



**THE DIFFUSION OF MODERN ENERGY TECHNOLOGIES
IN LOW-INCOME SETTINGS**

—

EVIDENCE FROM RURAL SUB-SAHARAN AFRICA

Dissertation zur Erlangung des akademischen Grades des
Doktors der Wirtschaftswissenschaften (Dr. rer. pol.) an der Universität Passau

vorgelegt von
Luciane Marlene Lenz
geboren in Leimen, Deutschland

Passau, August 2021

Erstgutachter: **Prof. Dr. Jörg Peters**
Zweitgutachter: **Prof. Dr. Michael Grimm**
Drittgutachter: **Prof. Dr. Ralf Kellner**
Disputation: 22.02.2022

Acknowledgments

I am very grateful to have grown up in a society that invests in its younger generations and scientific landscape. I benefited from it since day one. I am extremely grateful to have been born to the greatest parents and an extended family that empowered me to study with an ease that, I believe, is reserved to those with a loving and safe home. Thank you, Mama, Papa, the Lenz-Yildirims, Burkhardts, Müller-Wiarts, Härings, Diana, and Frau Ulrich. I thank you, Marcello, for being close by my side, for supporting me and cheering for me, in particular when I couldn't. Thanks to all my cool and supportive friends.

At RWI, I was surrounded by a small group of people that, I believe, do research to bring society forward and care about the phenomena and societies they study. I spent most of my – as they say – best years with Gunther, Julian, Jörg L., Jörg P., Maxie, and Lise. I know I was lucky to do so and will not forget these times. Thank you. I am grateful to Jörg, without whom I would have never started this thesis in the first place, to say the least. Jörg cared to go the extra mile in transmitting values and tools that go beyond publishing mantras and I am grateful for it.

I worked with, learned from, and very much enjoyed the company of some very nice and knowledgeable co-authors and colleagues at RWI, at the Development Economics chair in Passau – first and foremost Michael and Ann-Kristin –, at CRDES, IB&C Rwanda, and SETI. Thanks to, among others, Anicet, Anne, Ann-Kristin, Christiane Brüggemann, Diami, Emilie, Erin, Jana, Jonas, Marc, Mark, Medoune, Michael, Nathanael, Faraz, Leo, Ousmane, Samba.

Last but not least: thanks to all the hard-working interviewers. And, to come back to what all of this should mostly be about, thanks to all survey participants for their time and willingness to share; I hope the world gets cleaner, fairer, and better for you and all others.

I hope it became clear: the path towards this dissertation was challenging and colorful, full of far-away places, different realities, and inspiring people, and I am very grateful.

Acknowledgments Chapter 1

Data collection underlying this research was financially supported by the Center for Development Research in Bonn (ZEF) and the Federal Ministry for Economic Cooperation and Development (BMZ). Lenz, Peters, and Sievert gratefully acknowledge the support of a special grant (Sondertatbestand) from the German Federal Ministry for Economic Affairs and Energy and the Ministry of Innovation, Science, and Research of the State of North Rhine-Westphalia. The authors thank Anicet Munyehirwe and IB&C Rwanda for the implementation of the field work, and Jana Eßer, Ann-Kristin Reitmann, and Avery Maloney for valuable research assistance. The authors are grateful for valuable comments and suggestions by the editor, Jennifer Alix-Garcia, two anonymous referees, Gunther Bensch, Cyndi Berck, Chiara Kofol, Thomas Klug, Frank Otchere, and Colin Vance as well as participants at the Environment for Development (EfD) annual meeting in Shanghai, the Sustainable Energy Transition Initiative (SETI) annual meeting at Duke University, the CSAE Conference in Oxford, the NEUDC conference at Cornell, the 5th Green Growth Knowledge Platform conference, and research seminar participants at the World Bank Development Research Group in Washington D.C., at the University of the Witwatersrand in Johannesburg, ETH Zurich, University of Göttingen, University of Marburg, University of Groningen, Erasmus University Rotterdam, University of Mannheim, the ZEF Bonn, and the Development Network Berlin.

Acknowledgments Chapter 2

This research was primarily funded by the International Initiative for Impact Evaluation (3ie) with complementary funding from the German Federal Ministry of Education and Research (BMBF), and the Duke University Energy Initiative. We are thankful to 3ie for technical review and support throughout the study. We acknowledge excellent field work implementation by Samba Mbaye, Medoune Sall and colleagues at the Centre de Recherche pour le Développement Economique et Social (CRDES). We are grateful for expert advice from Birame Faye from the Government of Senegal, Christoph Messinger, Mireille Afoudji Ehemba, Viviane Sagna and the Energising Development Senegal team. We thank Jana Eßer, Emilie Bechtold and Daniela Breitmaier for excellent research assistance, and Ann-Kristin Reitmann, Marcello Pérez-Alvarez, and Gunther Bensch for excellent comments. Usmani gratefully acknowledges support from the Duke Global Health Institute and the Cornell Atkinson Center for Sustainability.

Acknowledgments Chapter 3

This research was financed by the International Initiative for Impact Evaluation (3ie) with complementary funding from the German Corporation for International Cooperation GmbH (GIZ), from the German Federal Ministry of Education and Research (BMBF), and from Duke University's Energy Initiative. I am particularly thankful to Jana Eßer, Ryan Chartier, Gunther Bensch, Marc Jeuland, and Moustapha Kane. Furthermore, I thank Ousmane Ndiaye, Maximiliane Sievert, Jörg Peters, Samba Mbaye, Sam Bentson, Alicia Obendorfer, Mats Hoppenbrouwers, and Marcello Perez-Alvarez for their valuable support. I also thank Medoune Sall, Nathanael Schmidt-Ott, Diamilatou Kane and the CRDES team for managing fieldwork. I am grateful for expert advice from Birame Faye, Christoph Messinger, Verena Brinckmann, Mireille Afoudji Ehemba, Viviane Sagna and the EnDev Senegal team, Issakha Youm from CERER Senegal. I furthermore thank anonymous 3ie referees for valuable comments.

Content

List of Figures	vi
List of Tables	viii
List of Abbreviations.....	x
Introduction	1
References Introduction	10
1 Demand for off-grid solar electricity – Experimental evidence from Rwanda ...	14
1.1 Introduction	14
1.2 Background	18
1.2.1 Policy background.....	18
1.2.2 Country background	20
1.3 Research approach and data	20
1.3.1 Off-grid technologies offered in experiment	20
1.3.2 Sampling.....	22
1.3.3 Survey implementation and the real-purchase bidding game.....	24
1.4 Results	27
1.4.1 Summary statistics and balancing test	27
1.4.2 Revealed WTP in bidding game.....	29
1.4.3 Effect of relaxing liquidity constraints	32
1.5 Interpretation of Results	33
1.5.1 The Sustainable Energy for All perspective	34
1.5.2 The Social planner’s perspective: A stylized cost benefit-analysis.....	35
1.6 Robustness of results: decliners and defaulters	38
1.6.1 Incidence	38
1.6.2 Adjusted willingness to pay estimate	40
1.6.3 Robustness of the effect of relaxing liquidity constraints	43
1.6.4 Implications for our key findings	44
1.6.5 Transaction costs	45
1.7 Conclusion.....	46
References Chapter 1.....	48
Appendix Chapter 1.....	53
Appendix 1A: Experiment Instructions.....	53
Appendix 1B: Declined purchase – Incidence and drivers.....	54
Appendix 1C: Payment defaults – Incidence and drivers.....	57
Appendix 1D: Decline and default – Robustness of the effect of relaxing liquidity constraints ..	61

Appendix 1E: Amortization periods.....	63
Appendix 1F: Main regression results.....	64
Appendix 1G: Learning and WTP.....	68
2 The supply side of technology diffusion – Evidence from rural Senegal.....	70
2.1 Introduction	70
2.2 Intervention	74
2.3 Conceptual rationale.....	77
2.4 Data	80
2.4.1 Sampling.....	81
2.4.2 Vendor, producer, and end-user surveys	84
2.4.3 Summary statistics and balancing.....	86
2.5 The Jambar market	86
2.5.1 Structure	86
2.5.2 Profitability of the firewood Jambar.....	89
2.6 Main empirical approach.....	91
2.7 Results	92
2.7.1 Treatment uptake	92
2.7.2 Impacts	93
2.7.3 Impact heterogeneity	96
2.7.4 Robustness.....	98
2.7.5 Impacts on upstream producers’ sales	100
2.7.6 Long-term impacts.....	101
2.7.7 Impacts on vendors’ louma-level sales of other stove types	104
2.7.8 Diffusion cost	105
2.8 Conclusion.....	107
References Chapter 2.....	110
Appendix Chapter 2.....	114
Appendix 2A: Introduction.....	114
Appendix 2B: Intervention	115
Appendix 2C: Data.....	117
Appendix 2D: The Jambar market	122
Appendix 2E: Robustness.....	123
Appendix 2F: Impact heterogeneity	129
Appendix 2G: Impacts on upstream producers’ sales	130
Appendix 2H: Impacts on vendor’s louma-level sales of other stoves	131
3 Housing ventilation and air pollution from biomass cooking.....	133
3.1 Introduction	133

3.2	Conceptual rationale.....	137
3.3	Systematic Literature Review.....	140
3.3.1	Study selection	140
3.3.2	Synthesis of results	141
3.4	Identification strategy and sampling	143
3.5	Measurements.....	147
3.6	Summary statistics.....	149
3.6.1	Explanatory factors.....	149
3.6.2	Kitchen air pollution and pollution exposures.....	150
3.7	Ventilation and kitchen pollution	152
3.7.1	Relationship.....	153
3.7.2	Contextualization.....	156
3.7.3	Robustness.....	157
3.8	Ventilation and women's pollution exposures	158
3.9	Conclusion.....	161
	References Chapter 3.....	164
	Appendix Chapter 3.....	169
	Appendix 3A: Systematic Review.....	169
	Appendix 3B: Data and measurement.....	177
	Appendix 3C: Descriptives.....	178
	Appendix 3D: Kitchen pollution	180
	Appendix 3E: Women's pollution exposure	187

List of Figures

Figure 1.1: Sectors surveyed and global horizontal irradiation levels.....	23
Figure 1.2: Participant Flow	24
Figure 1.3: Demand for solar kits.....	31
Figure 1.4: Payment over time by payment scheme and kit.....	40
Figure 1.5: Sensitivity of WTP to different decliner bias scenarios (in USD)	41
Figure 2.1: Main stove types offered in loumas	75
Figure 2.2: Stylized causal chain.....	79
Figure 2.3: Survey locations.....	80
Figure 2.4: Timeline of study components' roll-out.....	80
Figure 2.5: Louma sampling	82
Figure 2.6: Vendor sampling	83
Figure 2.7: Reported seasonality in sales (all products) in loumas and underlying reasons as occurred in 2019	88
Figure 2.8: Cost structure of the firewood Jambar retail price in loumas, as reported by vendors at baseline	90
Figure 2.9: Use of treatment elements for stove business, by experimental group	92
Figure 2.10: Vendors' average monthly firewood Jambar sales over time, by experimental group	95
Figure 2.11: Vendors' average monthly firewood Jambar sales, pre- and post-treatment by experimental group	97
Figure 2.12: Average absolute change in firewood Jambar sales between pre- and post-treatment months, by vendor and market location.....	98
Figure 2.13: Firewood Jambar market volume, by market actor.....	101
Figure 2.14: Vendors' average monthly firewood Jambar sales in the long run, by experimental group	102
Figure 2.15: Intervention cost per additional firewood Jambar sale, by experimental group	106
Figure 3.1: Stylized causal chain and intervention spectrum	138
Figure 3.2: Study selection flow chart.....	141
Figure 3.3: Air pollution and improved housing ventilation, significance and direction of effect in the literature.....	143
Figure 3.4: Community location.....	146
Figure 3.5: Kitchen classification illustrated by field photographs.....	148
Figure 3.6: Distribution of households across ventilation indicators	150
Figure 3.7: Cumulative distribution of PM _{2.5} kitchen pollution (Panel A) and pollution exposure (Panel B), by outdoor versus indoor cooking	152
Figure 3.8: Ventilation and kitchen pollution (PM _{2.5}), effect sizes in percent	153

Figure 3.9: Cumulative distribution of actual PM _{2.5} and hypothetical kitchen pollution assuming distinct kitchen ventilation conditions	156
Figure 3.10: Ventilation, kitchen location, and pollution exposure (PM _{2.5}), effect size in percent.....	161
Figure 1C.1: Share of final price paid for all kits, by community	60
Figure 2B.1: Village demand leaflet (anonymized)	115
Figure 2B.2: Marketing elements	116
Figure 2C.1: Vendor log sheet for bookkeeping	117
Figure 2C.2: Producer log sheet for bookkeeping	118
Figure 2C.3: Share of vendors reporting sales, by experimental group and month of call	119
Figure 2C.4: Total number of reporting months, by vendor	119
Figure 2D.1: Components of the Firewood Jambar retail price, as reported by producers at baseline	122
Figure 2E.1: Robustness of the main results to sequential inclusion of control variables	125
Figure 2E.1: Robustness of the main results to sequential inclusion of control variables	125
Figure 2F.1: Month-by-month impact of the intervention on monthly firewood Jambar sales, by treatment group.....	129
Figure 2H.1: Vendors' average monthly sales over time in the long run, by experimental group and stove type.....	131
Figure 3A.1: Geographical coverage of studies	173
Figure 3A.2: Ventilation indicators applied in studies	174
Figure 3B.1: Field photographs of MicroPEM and SUM measurements	177
Figure 3D.1: Median kitchen pollution and pollution exposure (PM _{2.5}), by percentiles	181
Figure 3D.2: Ventilation and 5th – 95.5th percentile kitchen pollution (PM _{2.5})	184

List of Tables

Table 1.1: Specifications of solar technologies	21
Table 1.2: Descriptive statistics and balancing test for randomized payment periods	28
Table 1.3: Bidding game outcomes	30
Table 1.4: Payment periods and WTP	33
Table 1.5: Cost and internalized benefits of off-grid electricity per household (in USD)	36
Table 1.6: Incidence of declining and default	39
Table 1.7: Adjusted WTP vs. bid (in USD).....	42
Table 1.8: Adjusted WTP vs. bid for buyers of Kit 3 (in USD)	43
Table 1.9: Payment periods and willingness to pay (controlling for defaulting and declining).....	44
Table 2.1: Intervention elements, by experimental group	77
Table 2.2: Study components	81
Table 2.3: Reporting regularity, by experimental group	84
Table 2.4: Impact of the intervention on vendors' marketing, by experimental group	93
Table 2.5: Impact of the intervention on vendors' monthly firewood Jambar sales	95
Table 2.6: Impact of the intervention on monthly firewood Jambar sales in the long run, by experimental group	103
Table 3.1: Potential confounders and their direction of impact	144
Table 3.2: Definition of ventilation indicators	148
Table 3.3: Summary statistics of kitchen pollution and pollution exposure (PM _{2.5})	151
Table 3.4: Ventilation and kitchen pollution (PM _{2.5}).....	153
Table 3.5: Effect sizes associated with change in ventilation, by ventilation indicator and in percent	154
Table 1B.1: Sales outcomes, by kit	54
Table 1B.2: Purchase decline, by kit and payment scheme.....	54
Table 1B.3: Winning of favorite kit among buyers and decliners, by kit	55
Table 1B.4: Bid of decliners versus buyers among winners, by kit	55
Table 1B.5: Drivers of declining, by kit.....	56
Table 1C.1: Propensity to pay (share of price effectively paid), by kit and payment period	57
Table 1C.2: Correlates of the payment share in monitoring phase, by kit	58
Table 1D.1: Payment periods and WTP (controlling for defaulting and declining)	62
Table 1E.1: Savings potential of solar kits	63
Table 1F.1: Detailed regression results of Table 5 - Payment periods and WTP.....	64
Table 1F.2: Detailed regression results of Table 5 restricted to sample without access to modern electricity - Payment periods and WTP	66

Table 1G.1: Summary statistics on pre-experiment solar kit exposure	68
Table 1G.2: Payment periods, WTP and former solar kit exposure.....	69
Table 2A.1: List of deviations from Pre-Analysis Plan.....	114
Table 2C.1: Balancing of vendor and business characteristics, at baseline.....	120
Table 2C.2: Socio-economic producer characteristics, at baseline	121
Table 2E.1: Impact of the intervention on vendors' marketing, any treatment group.....	123
Table 2E.2: Impact of the intervention on vendors' typical monthly sales	124
Table 2E.3: Robustness of main results to outliers	126
Table 2E.4: Impact of the intervention on vendors' marketing by experimental group, correcting for endline attrition using bounding exercise	127
Table 2E.5: Impact of the intervention on vendors' typical monthly sales of the firewood Jambar, correcting for endline attrition using bounding exercise	128
Table 2F.1: Characteristics of survey regions	129
Table 2G.1: Impact of the intervention on sales volume by producers and on joint sales volume by producers and vendors	130
Table 2H.1: Impact of the intervention on monthly sales of other stove types, by experimental group and time period (main monitoring and long-term)	132
Table 3A.1: Search string	169
Table 3A.2: Records in Systematic Review	170
Table 3A.3: Higher ventilation and pollution in Systematic Review, share of studies	176
Table 3B.1: Sample sizes, by measurement and year.....	177
Table 3B.2: Ventilation indicator, field categorisation and aggregation.....	177
Table 3C.1: Household, cooking, and measurement controls, by measurement sub-sample.....	178
Table 3C.2: Spearman monotone dependence between ventilation indicators	179
Table 3D.1: Ventilation and kitchen pollution (PM _{2.5}): composite ventilation indicators	180
Table 3D.2: Ventilation and kitchen pollution (PM _{2.5}): single ventilation indicators	182
Table 3D.3: Kitchen volume and kitchen pollution (PM _{2.5}), reduced sample and continuous volume specification.....	183
Table 3D.4: Ventilation and kitchen pollution (PM _{2.5}), with health covariates	185
Table 3D.5: Ventilation and kitchen pollution (PM _{2.5}), reduced sample.....	186
Table 3E.1: Correlates of behavioral smoke avoidance	187
Table 3E.2: Ventilation and pollution exposure (PM _{2.5}): composite ventilation indicators	188
Table 3E.3: Ventilation and pollution exposure (PM _{2.5}): single ventilation indicators	190
Table 3E.4: Ventilation and pollution exposure (PM _{2.5}), with health covariates	192

List of Abbreviations

ANOVA	Analysis of Variance
BDM	Becker-DeGroot-Marschak auction
BoP	Bottom-of-the-economic-Pyramid
CERER	Centre d'Études et de Recherches sur les Énergies Renouvelables
CES	Cooking Energy System
CO	Carbon Monoxide
DHS	Demographic and Health Surveys
DiD	Difference-in-Differences
EARP	Electricity Access Roll-Out Program
EnDev	Energising Development
FASEN	Foyers Améliorés au Sénégal (improved cookstoves in Senegal)
GEE	General Equilibrium Effects
HAP	Household Air Pollution
IAP	Indoor Air Pollution
IB&C	Inclusive Business and Consultancy
ICS	Improved Cookstove
IEA	International Energy Agency
IM	Information-Marketing Treatment
IMG	Information-Marketing-Grant Treatment
IR	Interval Regression
IT	Interim Target
LPG	Liquified Petroleum Gas
MicroPEMs	Micro Personal Exposure Monitors
MTF	Multi-Tier Framework for Measuring Access to Cooking Solutions
NIHR	National Institute for Health Research
OLS	Ordinary Least Squares
PAP	Pre-Analysis Plan
PAYG	Pay-As-You-Go
PC	Principal Component
PCA	Principal Component Analysis
PM	Particulate Matter
RCT	Randomized Controlled Trial
REG	Rwanda Energy Group
SACCOs	Savings and Credit Cooperative Organizations
SDG	Sustainable Development Goal
SEforALL	Sustainable Energy for All initiative
SHS	Solar Home System
SSA	Sub-Saharan Africa
SUM	Stove Use Monitor
WHO	World Health Organization
WTP	Willingness to Pay

Introduction

The relevance of energy technologies

The world is witnessing rapid technological advances that offer opportunities to reduce global poverty and environmental degradation. Technology includes all types of products, systems, or processes that allow us to live and produce better, at lower cost, faster, or more sustainably. It ranges from machinery in manufacturing plants, over know-how on the development of vaccines, to e-banking or crop planting systems. In the economic science, technology is widely accepted as a main driver of growth and socio-economic development, both in neoclassical growth theory (Solow 1956), and in empirical economics at the macro level (Comin and Hobijn 2010, Caselli and Coleman 2001, Keller 2004). At the micro scale, technologies are expected to be profitable for entrepreneurs, to increase welfare of consumers, or to reduce environmental degradation.

However, technologies diffuse only slowly in so-called Bottom-of-the-economic-pyramid (BoP) markets in poor and remote settings, despite constant technological advancement. This, on the one hand, confronts societies with the challenges and injustices associated with a rapidly widening gap in access to technologies (e.g., the “digital divide”) between richer and poorer countries, rural and urban areas, and genders (ECOSOC 2012). On the other hand, it offers massive opportunities for productivity, welfare, and environmental improvement.

One sphere of technological advancement is the energy sector. Energy is at the core of socio-economic development within our homes. Already in the late 1880’s, Thomas Edison recognized that one of our main uses of primary energy – electricity – “holds the secrets which will reorganize the life of the world” (Marden 1901, p.238). He should be proven right. In 2019, we consumed thirtyfold (173,340 TWh) the energy of that consumed in 1800 (5,653 TWh) (Smil 2017, Ritchie and Roser 2020) and diversified from exclusive reliance on biomass to various non-renewable (coal, oil, natural gas, and nuclear) and renewable energy sources (biomass, hydro, wind, geothermal, solar, and other). Both electricity and energy for cooking have since become indispensable in today’s modern homes.

Yet, in 2018, 789 billion people globally lacked access to electricity and 2.8 billion were deprived of access to clean cooking (IEA et al. 2020). A lack of electricity can restrain socio-economic development at the household level in multiple ways: by constraining domestic businesses and production, access to information and communication, and children’s education,

or by tying (mostly) women to time-intensive household tasks, limiting their educational and professional opportunities, and their agency more generally.

A lack of clean cooking, i.e., traditional cooking with solid fuels and inefficient cookstoves, substantially contributes to household air pollution (HAP) (Karagulian et al. 2015), the leading environmental cause of mortality, and thereby annually causes an estimated 3.8 million premature deaths. The health burdens are disproportionately shouldered by women and children (WHO 2016). Traditional cooking also poses a burden on forests and their ecosystem services (Bailis et al. 2015), and substantially contributes to global warming (IPCC 2014, Shindell et al. 2012) and loss of carbon sinks associated with fuel-related deforestation. Lastly, time-intensive fuel collection and inefficient cooking can, again, strain women's and children's time and opportunities (Köhlin et al. 2011).

Current energy access policies

To alleviate these multiple threats to livelihoods, health, and the environment, the international community has invested heavily to extend clean energy access to hitherto unconnected populations. In the 2010's, the UN launched the Sustainable Energy for All (SEforALL) initiative and dedicated the sustainable development goal (SDG) 7 to universal access to affordable, reliable, and modern energy by 2030. Yet, to reach universal access, there is a large spectrum of technologies, ranging from very simple to high-end solutions. This technological spectrum also provides a spectrum for alternative policy measures. It raises the question which technology to promote how and where, and to what extent to focus on wider or quicker diffusion of technologies at the expense of their quality or capacity. These questions must be answered considering highly constrained budgets of governments and target populations, and their heterogeneous contexts, preferences, and behaviors. Accordingly, there are vivid political debates, about how to increase access and use of both electricity and cooking energy.

In electricity policy, electric grid extension is a costly (Africon 2008, Lenz et al. 2017, Lee et al. 2019, Trotter et al. 2019, Chaplin et al. 2017), but a prestigious and highly visible policy measure long favored by national governments. Yet, in the last decades, remote and sparsely populated regions with an access deficit increasingly turned to smaller, off-grid technologies as a less costly alternative (IEA et. al 2020).

The debate on clean cooking is divided. Spearheaded by the World Health Organization (WHO), advocates of fully clean stove technologies disapprove of the promotion of technologies that emit (some) toxic pollutants and hence may be harmful to health. Advocates

of improved, yet not fully clean, stoves, by contrast, point to important co-benefits for the environment and women's time use produced by improved and locally adapted, affordable technologies that may serve as bridge technologies on a path to clean energy use (Simon et al. 2014, Bensch et al. 2015, Pattanayak et al. 2016, Hanna et al. 2016, Sambandam et al. 2015, Grieshop et al. 2011).

Energy access trends

While major investments have increased electricity access from 83 to 90 percent between 2010 and 2018, this global progress conceals large heterogeneity in progress across countries, and an urban-rural divide within countries. The global electricity access deficit is increasingly concentrated in Sub-Saharan Africa (SSA), home to nearly 70 percent of the global population without access in 2018 (IEA et al. 2020). This share is projected to increase to 90 percent by 2040 (IEA 2019). Even without considering likely disruptions of COVID-19 and COVID-19 policies, reaching universal access to electricity by 2030 is elusive. Challenges include population growth and complexities in reaching the remaining unserved last mile users, i.e., remote, low-income, or conflict-affected homes, where problems related to affordability, reliability, and delivery costs are amplified. Moreover, at the intensive margin, poor households with electricity access are observed to consume only little power, questioning the cost-effectiveness of large infrastructure investments, and hampering cost recovery of electricity providers (Chaplin et al. 2017, Lenz et al. 2017, Peters et al. 2011). Hopes are therefore pinned on off-grid solutions to reach last mile users. Access provided by solar-powered mini grids, for example, quintupled between 2010 and 2019. Yet, the evidence both on how to increase access and on how access actually impacts individuals and societies is inconclusive (e.g., Bayer et al 2020, Lee et al. 2020, Peters and Sievert 2016).

Reaching universal access to clean cooking is not less challenging, and we are projected to miss the universal access goal in 2030 by almost 30 percent (IEA et. al 2020). Again, progress has been disproportionally slow in SSA, where access rates were stagnant and population growth is high: between 2010 and 2018, the number of people without access in the region has therefore increased from 750 million to 890 million (IEA et. al 2020). The continent is projected to be home to 50 percent of people without clean cooking access in 2040 (IEA 2019). Challenges to dissemination are manifold, including underdeveloped supply chains (Lewis et al. 2015, Pattanayak et al. 2019), poor durability or sustainability (Hanna et al. 2016), misalignment of consumer preferences with available improved technologies, and low valuation of the benefits these technologies provide (Mobarak et al. 2012, Jeuland et al. 2015, Jeuland et al. 2014,

Jeuland and Pattanayak 2012). Many challenges are aggravated in rural areas due to shallow markets (Lewis and Pattanayak 2012, Jeuland et al. 2015), poverty, and lower fuel scarcity (Jagger and Perez-Heydrich 2016). Accordingly, the evidence on the dissemination and the actual benefits of clean cooking energy in poor households in the global south is very mixed (Pope et al. 2017, Jeuland et al. 2021).

Contribution

This collection of three chapters responds to today's energy challenges. It explores innovative policy aimed to equip the energy poor with access to improved cooking energy and electricity, looking both at the demand and supply side of modern energy technologies. Concretely, it discusses mechanisms to increase uptake of off-grid solar electricity in rural Rwanda based on experimental demand measurements (Chapter 1), it studies how to diffuse improved cooking technologies in rural Senegal via supply-side mechanisms (Chapter 2), and it identifies the need to target cooking technologies in consideration of the broader household context in rural Senegal and beyond (Chapter 3). This thesis thereby studies a range of important mechanisms ranging from financial (Chapter 1 and 2) over informational (Chapter 2) treatments to context analysis (Chapter 3). The chapters share multiple commonalities. First, all three chapters make use of own-collected primary data from field studies among people suffering most from the current energy-access gap, i.e., rural populations in East and West Africa. Second, they make use of well-tailored, quantitative methodologies to identify causal relationships, both in experimental and quasi-experimental setups. Third, most of these research designs were pre-specified (Chapter 2 and 3), enhancing credibility and transparency of the findings. Fourth, two of the studies use auction designs to quantify the willingness to pay (WTP) for technologies (Chapter 1 and 2). Fifth, the estimation of point estimates on key study outcomes in each chapter is complemented by thorough analyses of descriptive data to embed findings within their contexts and improve our understanding of populations and preferences for which data is scarce and our collective knowledge limited. Lastly, the three chapters are primarily motivated by their political and socio-economic relevance, and all contribute to ongoing debates about alternative energy policy choices, or, more concretely, the trade-offs between implementing achievable, transitory policies versus more ambitious, longer-term policies.

I shortly elaborate on the latter before outlining the three chapters in more detail. Goals of international energy policy are rightfully ambitious in striving for prompt and universal access to clean, sustainable, and modern electricity and cooking technologies. This dissertation, however, argues that low-cost, transitory solutions are required on the path towards these

ultimate goals. Importantly, this holds only in a context of financially constrained households and governments, assuming that resources are limited, and that unmet, essential needs are manifold. Second-best, lower-tier solutions are not always popular. Simple electricity technologies do not enable people to benefit from many basic welfare-improving services, such as using larger machinery to improve businesses, or cooling food. The same is true for clean air, recognized as a human right (Human Rights Council 2019), which simple improved cooking stoves cannot deliver. However, I provide empirically founded arguments in favor of such intermediary solutions. They should be understood as pragmatic responses to the last decade's slow progress in increasing the use of clean stoves (Chapter 2 and 3) and to challenges in reaching the last mile of electricity consumers paired with typically low use of electricity by poor households once available (Chapter 1). Transitory solutions provide low-cost improvements in contexts where quick solutions are required and highly constrained budgets of both national governments and target populations face difficult trade-offs between multiple basic needs and services. All three chapters and their findings thereby evolve around questions of efficient allocation of scarce resources, a question that is at the core of the economic science.

Chapter 1: Demand for off-grid solar electricity – Experimental evidence from Rwanda

With Michael Grimm, Jörg Peters, and Maximiliane Sievert

This chapter studies the WTP for three off-grid solar technologies by means of a Becker-DeGroot-Marschak (BDM) auction among 323 randomly selected households in 16 remote and poor, off-grid communities in Rwanda. It thereby complements Lee et al.'s (2019) quantification of demand for grid electricity at the opposite, lower bound of the technological spectrum, i.e., basic solar kits whose services range from just one task light to several lighting sources, mobile phone charging, and radio usage. In addition, this analysis uses the random assignment of households to a payment period of one week, six weeks, or five months to test the effect of a zero-interest rate credit scheme on WTP.

We find, first, that the median WTP for the three solar kits is between 30 and 41 percent of their respective market prices. This WTP is considerable relative to the low expenditure levels in this resource-poor setting, signaling a high preference for the technologies. Yet, even at the upper tail of the income distribution, only few households reveal a WTP that reaches market prices. Second, we find that relaxing liquidity constraints from a one-week payment period to either six weeks or five months increases the WTP by at most 13 percent. Once we account for interest rates, this increase in WTP does not cover transaction costs associated with a credit-based

financing scheme. We show that these findings are qualitatively robust to adjusting our WTP estimates for declined purchases and incomplete payments.

We then interpret our findings from two perspectives. Taking the perspective of the SEforALL initiative, we suggest that most of the rural poor will not be able to pay cost-covering prices for off-grid solar technologies. This challenges the expectation that free markets and pay-as-you-go (PAYG) payment schemes alone will help reach poor, last mile consumers and, correspondingly, the goal of universal electricity access.

Taking a Social Planner's perspective, we conduct a stylized welfare assessment of a solar electricity subsidization policy. We find that the benefits internalized by solar kit buyers, as reflected in their WTP, do not cover the costs of off-grid solar electrification. Public subsidies to close this *internal return on investment* gap would hence only be justified if non-internalized benefits are sufficient to close this gap, i.e., external effects and long-term or unknown private benefits that are not reflected in the WTP. The existing literature suggests the effects of small off-grid solar are generally positive, but there is no indication of an effect on transformative economic development. Yet, compared to on-grid electrification, non-internalized benefits of off-grid solar plausibly close a larger part of this *internal return on investment* gap given the high costs of grid extension. We therefore conclude that, if universal electrification is a political goal, subsidized off-grid solar is the preferable technology to reach much of Africa's rural poor.

Chapter 2: The supply side of technology diffusion – Evidence from rural Senegal

With Marc Jeuland, Ousmane Ndiaye, Jörg Peters, Maximiliane Sievert, and Faraz Usmani

This chapter studies the role of supply chains for the diffusion of beneficial technologies in so-called Bottom-of-the-economic-Pyramid (BoP) markets in the Global South. While the micro-economic literature has considerably studied demand-side constraints to the oftentimes slow diffusion of technologies (see Foster and Rosenzweig 2010 for a review), evidence on supply-side constraints is scant.

This chapter uses surveys of an entire technology market in rural Senegal, including 215 producers of improved cookstoves (ICS) in urban areas, 127 intermediary vendors of ICS in rural markets, and over 900 end-users in 60 remote villages. It tests how the relaxation of informational and financial constraints among ICS vendors facilitates diffusion of ICS by means of a randomized controlled trial (RCT) and monthly tracking of ICS sales over a period of roughly 20 months. This study responds to prior research, which has identified a WTP for

the ICS in rural villages that exceeds the stoves' price in urban areas (Bensch and Peters 2020), in light of which it is puzzling that diffusion of the ICS remains low in these areas.

We show that vendors randomly assigned to a treatment including information on downstream demand, upstream producer contacts, a set of marketing materials, and a grant of USD 31 unconditionally earmarked for stove transport sold approximately 0.9 more ICS per month following the intervention than control vendors. This is a statistically significant effect compared to 0.08 stoves per month sold by all vendors in pre-intervention months. This effect is small in absolute but large in relative terms, increasing sales 11.25 times relative to control vendors' sales. Yet importantly, the intervention was only effective if it included the grant component. As a potential mechanism behind these increased sales, we find that treated vendors expanded their marketing activities much more than control vendors. Importantly, we show that these effects remain two years after the intervention despite market disruptions from COVID-19 policies.

We descriptively show large heterogeneity in impact across regions and individual vendors, i.e., a few super-sellers drive most of the observed impacts. This analysis shows that context and targeting are crucial, and is broadly in line with the evidence on informal sector heterogeneity (e.g., Grimm et al. 2012, Cunningham and Maloney 2001) and on microfinance, showing that some entrepreneurs better transform (financial) support into business growth (e.g., Meager 2019, Fiala 2018, De Mel et al. 2008). However, increased sales of market vendors do not translate into detectable increases in sales reported by upstream producers. This is not surprising given that the additional firewood ICS sold by vendors constitute a small share of producers' nationwide sales.

Lastly, we show that our treatment has cross-product externalities, affecting vendors' sales of other ICS types, thereby generating important co-benefits. While conceptually possible, we do not find negative nor positive effects on vendors' sales of traditional stoves. This is potentially due to the small effect sizes in absolute terms. Yet, we anyhow underline that a policy tool based on cooperation with the private sector needs to manage incentives thoroughly, as negative side effect, such as increased sales of products that are detrimental from a societal or environmental perspective, may emerge.

Taken together, our intervention provides evidence on the potential of supply-side policy tools targeting established market actors to meet latent demand for welfare-improving technologies, such as ICS, in rural settings. This is an innovative, relatively low-cost approach to increasing

technology diffusion. In this sense, while effect sizes suggest that additional (demand-side) interventions are required to boost large-scale diffusion of the firewood ICS, the present study is a successful proof-of-concept.

Chapter 3: Housing ventilation and air pollution from biomass cooking

Single-authored

This chapter presents improved housing ventilation as a transitory solution on the path towards universal clean cooking. Keeping emissions constant, better ventilated housing will reduce the concentration of HAP per unit of area, and in turn people's exposure to pollution. I substantiate the validity of this claim in two ways.

First, I conduct a pre-registered systematic review of the scientific literature on housing ventilation and cooking-related air pollution in low- and middle-income countries. Systematic searches in 13 databases identified 60 published papers from health and environmental sciences, which, in the aggregate, point to a negative relationship. The share of studies that find significant pollution reductions is not less promising than the shares found in recent systematic reviews of ICS studies (Pope et al. 2020, Jeuland et al. 2021). Yet, there is little consensus on how to measure ventilation, and most estimations are methodologically weak or insufficiently grounded in theory (also see Barnes 2014).

Second, this chapter quantifies the influence of kitchen ventilation on $PM_{2.5}$ ¹ kitchen pollution and women's $PM_{2.5}$ personal exposure, as measured twice for 24 hours in households from 15 rural communities in northern and central Senegal. The pooled ordinary least squares (OLS) analysis aggregates two rounds of detailed panel data, resulting in 419 household-year observations with measurement of women's pollution exposures, and 220 household-year observation with measurement of kitchen pollution. I conduct multiple tests to assess the robustness of my findings, and, in sum, my analysis is able to overcome major limitations of the existing evidence. I observe massive average pollution levels in kitchens, which substantially exceed the WHO's safe levels ($530\mu g/m^3$ $PM_{2.5}$ versus $10\mu g/m^3$ $PM_{2.5}$, see WHO 2006). Yet, cooking in fully ventilated (i.e., open air) or substantially ventilated kitchens, is associated with 56-75 or 16-50 percent less kitchen pollution relative to unventilated kitchens, respectively. Both associations are statistically significant and highly relevant considering the high absolute pollution levels. These pollution reduction potentials are also comparable to what

¹ $PM_{2.5}$ is very small, airborne fine particulate matter (with a diameter less than 2.5 micrometres) that originates from combustion processes. It is damaging to human health, as it can pass the respiratory tract and consequently penetrate small body airways, lungs, and bloodstreams.

the evidence suggests for improved stoves (Pope et al. 2020), or for clean stoves given typical levels of stove stacking (Jeuland et al. 2018), i.e., the use of clean stoves alongside traditional stoves.

Moreover, I find that the average pollution exposure of women is highly harmful ($134 \mu\text{g}/\text{m}^3$ $\text{PM}_{2.5}$), but substantially lower than kitchen pollution. I show that this exposure is not observably affected by housing ventilation. This apparent contradiction may reflect that I do not capture all drivers of women's exposure. Alternatively, it may mirror selective, behavioral risk reduction by women involved in cooking in highly polluted kitchens, for which I provide some tentative support. This finding questions whether policy should focus on reducing kitchen concentrations as opposed to pollution exposures.

Given slow, or even negative, progress towards meeting universal clean cooking, my findings are critical for designing and targeting transitory policies that complement clean cooking programs. They imply, first, that policy can target ventilation to reduce air pollution in homes. Second, targeting of cookstoves should consider housing ventilation. On the one hand, fully clean stoves have plausibly higher pollution reduction potentials in households with poorly ventilated kitchens. On the other hand, low-cost improved stoves combined – or targeted to households – with highly ventilated kitchens may be a cost-effective interim solution (for similar claims see Langbein et al. 2017 and Teune et al. 2020). Third, ICS research needs to systematically control for housing ventilation. Fourth, my findings support the spirit of some initiatives (such as the cooking energy system, CES) in calling for a more holistic view of the cooking environment, and understanding technologies, fuels, housing, and cooking culture in unity.

References Introduction

Africon. 2008. Unit Costs of Infrastructure Projects in Sub-Saharan Africa. *Background Paper 11, Africa Infrastructure Sector Diagnostic*. World Bank, Washington, DC.

Bailis, Robert, Rudi Drigo, Adrian Ghilardi, and Omar Masera. (2015). The carbon footprint of traditional woodfuels. *Nature Climate Change*, 5(3), 266-272.

Barnes, Brendon R. 2014. Behavioural Change, Indoor Air Pollution and Child Respiratory Health in Developing Countries: A Review. *International Journal of Environmental Research and Public Health* 11(5): 4607-4618.

Bayer Patrick, Ryan Kennedy, Joonseok Yang, and Johannes Urpelainen. 2020. The need for impact evaluation in electricity access research. *Energy Policy* 137: 111099.

Bensch, Gunther, and Jörg Peters. 2015 The intensive margin of technology adoption – experimental evidence on improved cooking stoves in rural Senegal. *Journal of Health Economics* 42: 44–63.

Bensch, Gunther, and Jörg Peters. 2020. One-off grants and long-run adoption – Experimental evidence on improved cooking stoves in Senegal. *American Journal of Agricultural Economics* 102(1): 72-90.

Caselli, Francesco, and Wilbur John Coleman. 2001. Cross-Country Technology Diffusion: The Case of Computers. *American Economic Review* 91(2): 328-335.

Chaplin, Duncan, Arif Mamun, Ali Protik, John Schurrer, Divya Vohra, Kristine Bos, ..., and Thomas Cook. 2017. Grid Electricity Expansion in Tanzania by MCC: Findings from a Rigorous Impact Evaluation. Washington, DC: Mathematica Policy Research.

Comin, Diego, and Bart Hobijn. 2010. An exploration of technology diffusion. *American Economic Review* 100(5): 2031-59.

Cunningham, Wendy V., and William F. Maloney. 2001. Heterogeneity among Mexico's microenterprises: An application of factor and cluster analysis. *Economic Development and Cultural Change* 50(1): 131-156.

De Mel, Suresh, David McKenzie, and Christopher Woodruff. 2008. Returns to capital in microenterprises: evidence from a field experiment. *The Quarterly Journal of Economics* 123(4): 1329-1372.

ECOSOC. 2012. Progress made in the implementation of and follow-up to the outcomes of the World Summit on the Information Society at the regional and international levels. https://unctad.org/system/files/official-document/a74d62_en.pdf

Fiala, Nathan. 2018. Returns to microcredit, cash grants and training for male and female microentrepreneurs in Uganda. *World Development* 105: 189–200.

Foster, Andrew D., and Mark. R. Rosenzweig. 2010. Microeconomics of technology adoption. *Annual Review of Economics* 2(1): 395-424.

Grieshop, Andrew P., Julian D.Marshall, and Milind Kandlikar. 2011. Health and climate benefits of cookstove replacement options. *Energy Policy* 39(12): 7530-7542.

Grimm, Michael, Peter Knorringa, and Jann Lay. 2012. Constrained Gazelles: High Potentials in West Africa's Informal Economy. *World Development* 40(7): 1352-1368.

Hanna, Rema, Esther Duflo, and Michael Greenstone. 2016. Up in smoke: the influence of household behavior on the long-run impact of improved cooking stoves. *American Economic Journal: Economic Policy* 8(1): 80-114.

Human Rights Council. 2019. Issue of human rights obligations relating to enjoyment of a safe, lean, health and sustainable environment – Report of the Special Rapporteur. <https://www.ohchr.org/EN/Issues/Environment/SREnvironment/Pages/CleanAir.aspx>

IEA (International Energy Agency). 2019. Africa Energy Outlook 2019: World Energy Outlook special report. IEA, Paris. <https://www.iea.org/reports/africa-energy-outlook-2019>.

IEA, IRENA, UNSD, World Bank, and WHO. 2020. Tracking SDG 7: The Energy Progress Report. World Bank, Washington DC.

IPCC (International Panel on Climate Change). 2014. Summary for policymakers. In: *Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Edenhofer, O., R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Baum, S. Brunner, P. Eickemeier, B. Kriemann, J. Savolainen, S. Schlömer, C. von Stechow, T. Zwickel and J.C. Minx (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Jagger, Pamela, and Carolina Perez-Heydrich. 2016. Land use and household energy dynamics in Malawi. *Environmental Research Letters* 11(12): 125004.

Jeuland, Marc A., and Subhrendu K. Pattanayak. 2012. Benefits and costs of improved cookstoves: assessing the implications of variability in health, forest and climate impacts. *PLOS ONE* 7(2): e30338.

Jeuland, Marc, Subhrendu K. Pattanayak, and Jie Sheng Tan Soo. 2014. Preference Heterogeneity and Adoption of Environmental Health Improvements: Evidence from a Cookstove Promotion Experiment. Available at SSRN: <https://ssrn.com/abstract=2490530>.

Jeuland, Marc, Subhrendu K. Pattanayak, and Randall Bluffstone. 2015. The economics of household air pollution. *Annual Review of Resource Economics* 7(1): 81-108.

Jeuland, Marc A., Jie-Sheng Tan Soo, and Drew Shindell. 2018. The need for policies to reduce the costs of cleaner cooking in low income settings: Implications from systematic analysis of costs and benefits. *Energy Policy* 121: 275-285.

Jeuland, Marc A., T Robert Fetter, Yating Li, and Subhrendu K Pattanayak. 2021. Is energy the golden thread? A systematic review of the impacts of modern and traditional energy use in low-and middle-income countries. *Renewable and Sustainable Energy Reviews* 135:110406.

Karaguliana, Federico, Claudio A. Belis, Carlos Francisco C. Dora, Annette M. Prüss-Ustün, Sophie Bonjour, Heather Adair-Rohani, and Markus Amann. 2015. Contributions to cities' ambient particulate matter (PM): A systematic review of local source contributions at global level. *Atmospheric Environment* 120: 475-483.

Keller, Wolfgang. 2004. International technology diffusion. *Journal of Economic Literature* 42(3): 752-782.

Köhlin, Gunnar, Erin O. Sills, Subhrendu K. Pattanayak, and Christopher Wilfong. (2011). Energy, gender and development: what are the linkages? Where is the evidence? *The World Bank Policy Research Working Paper*, 5800.

Langbein, Jörg, Jörg Peters, and Colin Vance. 2017. Outdoor cooking prevalence in developing countries and its implication for clean cooking policies. *Environmental Research Letters* 12(11): 115008.

Lee, Kenneth, Edward Miguel, and Catherine Wolfram. 2019. Experimental evidence on the economics of rural electrification. *Journal of Political Economy* 128(4): 1523-1656.

Lee, Kenneth, Edward Miguel, and Catherine Wolfram. 2020. Does Household Electrification Supercharge Economic Development? *Journal of Economic Perspectives* 34(1): 122-44.

- Lenz, Luciane, Anicet Munyehirwe, Jörg Peters, and Maximiliane Sievert.** 2017. Does large scale infrastructure investment alleviate poverty? Impacts of Rwanda's electricity access roll-out program. *World Development* 89: 88-110.
- Lewis, Jessica J., and Subhrendu K. Pattanayak.** 2012 Who adopts improved fuels and cookstoves? A systematic review. *Environmental Health Perspectives* 120: 637-45.
- Lewis, Jessica J., Vasundhara Bhojvaid, Nina Brooks, Ipsita Das, Marc A. Jeuland, Omkar Patange, and Subhrendu K. Pattanayak.** 2015. Piloting Improved Cookstoves in India, *Journal of Health Communication* 20(sup1): 28-42.
- Marden, Orison Swett.** 1901. How they Succeeded.
- Meager, Rachael.** 2019. Understanding the Average Impact of Microcredit Expansions: A Bayesian Hierarchical Analysis of Seven Randomized Experiments. *American Economic Journal: Applied Economics* 11(1): 57-91.
- Mobarak, Ahmed Mushfiq, Puneet Dwivedi, Robert Bailis, Lynn Hildemann, and Grant Miller.** 2012. Low demand for nontraditional cookstove technologies. *Proceedings of the National Academy of Sciences of the United States of America* 109(27): 10815-10820.
- Pattanayak, Subhrendu K., Marc Jeuland, Jessica Lewis, Faraz Usmani, Nina Brooks, Vasundhara Bhojvaid, ... and Veerabhadran Ramanathan.** (2019). Experimental evidence on promotion of electric and improved biomass cookstoves. *Proceedings of the National Academy of Sciences*, 116(27), 13282-13287
- Peters, Jörg, Collin Vance, and Marek Harsdorff.** 2011. Grid extension in rural Benin: Micro-manufacturers and the electrification trap. *World Development* 39(5): 773-783.
- Peters, Jörg, and Maximiliane Sievert.** 2016. Impacts of Rural Electrification Revisited – The African Context. *Journal of Development Effectiveness* 8 (3): 327-45.
- Pope, Daniel, Nigel Bruce, Mukesh Dherani, Kirstie Jagoe, and Eva Rehfuss.** 2017. Real-life effectiveness of ‘improved’ stoves and clean fuels in reducing PM2.5 and CO: systematic review and meta-analysis. *Environment International* 101: 7-18.
- Pope, Daniel, Michael Johnson, Nigel Fleeman, Kirstie Jagoe, Rui Duarte, Michelle Maden, Ramona Ludolph, ... and Jessica J. Lewis.** 2020. Are cleaner cooking solutions clean enough? A systematic review and meta-analysis of particulate and carbon monoxide concentrations and exposures. Unpublished manuscript.
- Ritchie, Hannah, and Max Roser.** 2020. Access to Energy. *Our World in Data*. <https://ourworldindata.org/energy-access>.
- Sambandam, Sankar, Kalpana Balakrishnan, Santu Ghosh, Arulselvan Sadasivam, Satish Madhav, Rengaraj Ramasamy, ..., and Veerabhadran Ramanathan.** 2015. Can currently available advanced combustion biomass cook-stoves provide health relevant exposure reductions? Results from initial assessment of select commercial models in India. *EcoHealth* 12(1): 25-41.
- Shindell, Drew, Johan C. Kuylensstierna, Elisabetta Vignati, Rita van Dingenen, Markus Amann, Zbigniew Klimont, ... and David Fowler.** (2012). Simultaneously mitigating near-term climate change and improving human health and food security. *Science*, 335, 183-189.
- Simon, Gregory L., Rob Bailis, Jill Baumgartner, Jasmine Hyman, and Arthur Laurent.** 2014. Current debates and future research needs in the clean cookstove sector. *Energy for Sustainable Development* 20: 49-57.
- Smil, Vaclav.** 2017. Energy Transitions: Global and National Perspectives. Santa Barbara, California: ABC-CLIO, LLC

Solow, Robert M. 1956. A contribution to the theory of economic growth. *The Quarterly Journal of Economics* 70(1): 65-94.

Teune, Bastiaan, Hoang Thanh Ha, Daniel Salinas, Kevin McLean, and Rob Bailis. 2020. Low-cost interventions to reduce emissions and fuel consumption in open wood fires in rural communities. *Energy for Sustainable Development*, 58: 119-128.

Trotter, Philipp. A., Nathaniel J. Cooper, and Peter R. Wilson. 2019. A multi-criteria, long-term energy planning optimisation model with integrated on-grid and off-grid electrification—The case of Uganda. *Applied Energy* 243: 288-312.

WHO (World Health Organization). (2014). WHO indoor air quality guidelines: household fuel combustion. World Health Organization, Geneva.

WHO (World Health Organization). 2016. Burning opportunity: clean household energy for health, sustainable development and wellbeing of women and children. World Health Organization. <https://apps.who.int/iris/handle/10665/204717>.

1 Demand for off-grid solar electricity – Experimental evidence from Rwanda

With Michael Grimm, Jörg Peters, and Maximiliane Sievert

1.1 Introduction

Universal electricity access is a primary goal of governments in the Global South and the international community. The sustainable development goals (SDGs) and the United Nations' initiative 'Sustainable Energy for All' (SEforALL) call for connecting the nearly one billion people worldwide hitherto lacking electricity access by 2030. Yet, the impacts of electricity access on economic development remain unclear. It is beyond discussion that the economic transition in industrialized countries would not have been possible without grid-based electrification. However, the right timing of electrification in developing countries, particularly in remote and sparsely populated areas, is under debate, given high investment costs and often modest short-term impacts. For Asian and Latin American countries, Lipscomb et al. (2013), Litzow et al. (2019), Rud (2012), van de Walle et al. (2017), Kassem (2019), and Khandker et al. (2013) find positive effects on various socio-economic outcomes. In Africa, by contrast, it is less clear whether electrification triggers massive economic development (Bernard 2012, Bos et al. 2018, Chaplin et al. 2017, Dinkelman 2011, Lee et al. 2019, Lenz et al. 2017, Peters and Sievert 2016). At the same time, the cost of electrification is substantial. The International Energy Agency (IEA) estimates that, for Africa alone, the investment required to achieve universal access by 2030 is 31 billion USD annually (IEA 2017), which corresponds to 70 percent of the total yearly official development assistance sent to the continent (World Development Indicators 2018).

Only recently, researchers have started questioning whether public funds should be used to subsidize mass electrification. Especially in developing countries, tight governmental budgets are up against various underfinanced public services, such as transport, health and education, and infrastructure. This is prominently illustrated by Lee et al. (2019), who randomized different connection fees across villages in Western Kenya to obtain households' revealed willingness to pay (WTP) for *grid* access. Because the observed WTP covers only a small part of the required cost, they suggest that electrification creates a 'social surplus loss' ranging between 593 and 935 USD per household. Lee et al. (2019) acknowledge that the WTP is

constrained in a context of high poverty and imperfect capital markets. Moreover, a revealed WTP reflects only internalized benefits. Yet, the authors show that non-internalized private and social benefits are unlikely to justify subsidies on this order of magnitude.

In the present chapter, we complement Lee et al. (2019) by studying the revealed WTP for three different *off-grid* solar technologies. While Lee et al. (2019) provide novel insights on the demand for electrification at the upper bound of the technological spectrum, we add to this by studying demand for electrification at the lower bound and contribute to the emerging literature on the WTP for different electricity technologies in different contexts (Burgess et al. 2019, Sievert and Steinbuks 2019, Yoon et al. 2014).

Investment costs for the solar kits we offered vary between 13 and 180 USD. Unlike on-grid electrification, off-grid electricity does not require large-scale infrastructure investments, such as power plants and transmission lines. At the same time, service levels are lower for off-grid than for on-grid connections. The solar kits used in this chapter allow for different energy usage levels ranging from just one task light to several lighting sources, mobile phone charging, and radio usage. They cannot power high-wattage appliances like machinery, electric stoves, fridges, or irons.² This can become a bottleneck for productivity development in some places. Yet, evidence from previous studies suggests that even if the grid is available, electricity consumption levels are typically low. For example, electricity is virtually never used for cooking or refrigeration in households, and machinery usage by enterprises is rare (see, for example, Chaplin et al. 2017, Lenz et al. 2017, Neelsen and Peters 2011, Peters et al. 2011, and Taneja 2018). Electricity demand can hence mostly be met by off-grid technologies.

Using a sample of 323 randomly selected households in 16 remote and poor off-grid communities spread across rural Rwanda, we elicit the WTP for three different types of off-grid solar – a 0.5 Watt, a 3.3 Watt, and a 20 Watt device – by means of a Becker-DeGroot-Marschak (BDM) real-purchase bidding game. In addition, each household was randomly assigned to a payment period of one week, six weeks, or five months in order to test for the effect of a zero-interest rate credit scheme on the WTP.

² For the sake of simplicity, our comparison of different electricity supplies ignores decentralized mini-grids that are powered by solar, wind, hydro, or diesel generators. Depending on their scale, they allow for higher power services, but incur high upfront investment costs for distribution lines as well as generation and storage capacities. Our argument is robust to the inclusion of mini-grids, since their cost structure is similar to the Lee et al. (2019) cost estimates, which include only transformers and distribution lines. See Fowlie et al. (2019) and Peters et al. (2019) for a discussion of the viability and challenges of mini-grid electrification.

First, we find that the median WTP for the three solar kits is between 30 and 41 percent of their respective market prices. While this is considerable relative to the low total expenditure level in this poor setting, even at the upper tail of the income distribution, few households reveal a WTP that comes close to market prices. This observation contributes to the broader literature on the adoption of socially desirable technologies. In recent years, many studies have shown, mostly for health-improving technologies, that demand is highly price elastic (see Bensch et al. 2015, Cohen and Dupas 2010, Dupas 2014, Tarozzi et al. 2014, Kremer and Miguel 2007, Mobarak et al. 2012, Pattanayak et al. 2019). The similarity between these technologies and electricity is that benefits are not fully internalized, providing a justification for policy to foster adoption. This branch of literature strongly advocates ‘cost-sharing’ dissemination strategies that subsidize end-user prices to raise adoption rates to a socially desirable level (Ahuja et al. 2015, Bates et al. 2012).

Second, we find that relaxing liquidity constraints from a one-week payment period to either six weeks or five months increases the WTP by at most 13 percent. Accounting for interest rates shows that this increase in WTP is not enough to cover transaction costs that would be associated with a credit-based financing scheme such as the highly praised pay-as-you-go (PAYG) schemes. This result challenges the market-based paradigm, which SEforALL and most programs pursue, by expecting the largely poor target group to pay cost-covering prices for off-grid solar technologies. While the affordability problems of the poor are well known, the common hypothesis is that people’s WTP is high enough, but liquidity constraints hamper adoption (see Abdul-Salam and Phimister 2019, Urpelainen and Yoon 2017).

We thereby also contribute to the literature on liquidity constraints and technology adoption (see, for example, Bauchet and Morduch 2019, Beltramo et al. 2015, Ben Yishay et al. 2017, Devoto et al. 2012, Guiteras et al. 2016, Levine et al. 2018, Tarozzi et al. 2014, and Yoon et al. 2016). This literature suggests that micro-loans or extended payment periods increase adoption in poor settings, sometimes considerably. More specifically, our chapter builds on the work by Yoon et al. (2016) who study the WTP for a small solar lamp in India and randomly vary a standard offer, a trial period, and a trial period with postponed payment. The authors find that the overall WTP is very low (at less than 10 percent of the market price), and while the trial period alone has no effect, the extended payment period increases the WTP by 17 percent. Our chapter goes further in that we examine the WTP for three differently sized solar kits. Our smallest kit is similar to the Yoon et al. lamp but offers more lighting hours per day (6.5 vs. 2). The other two kits are of higher quality in terms of both luminosity and daily lighting hours.

Moreover, off-grid solar has a different role in remote areas in Africa, as most of rural India is within the reach of the grid, making solar a less attractive alternative (Fowlie et al. 2019).

An inherent challenge of real-purchase offer experiments is participants who decline to purchase after a successful bid and buyers who default on their payment. Declining and defaulting raises concerns about the accuracy of submitted bids. In our case, 15 percent of successful bidders declined to purchase, and 34 percent of buyers did not make full payments. We discuss the implications for our findings in detail, provide adjusted estimates of the WTP to account for declining and defaulting (following the approach used in Ben Yishay et al. 2017), and show that the main results are robust to these challenges. Our analysis thereby also serves as a conceptual example of how to empirically approach such challenges in real-purchase offer experiments.

We then interpret our findings from two perspectives. In Section 1.5.1, we examine whether households in poor and remote areas – a considerable portion of the nearly one billion without electricity – can afford to pay cost-covering prices for off-grid solar (referred to as *SEforALL perspective*). In Section 1.5.2, we examine whether a full subsidization policy would be desirable from a welfare-oriented public policy perspective (the *Social Planner's perspective*).

The *SEforALL perspective* suggests that the majority of the rural poor will not be able to pay cost-covering prices for off-grid solar technologies. *M-Kopa*, *BBOX* and *d.light* are examples of successful solar companies with high sales numbers in Kenya, Tanzania, and Ethiopia (Lighting Global 2016), and more recently also in Rwanda (Lighting Global 2018). Our findings do not challenge their business case, because the better-off strata of those countries can afford to buy these products. Rather, we emphasize that market-based approaches will have difficulties in reaching Africa's rural poor and, correspondingly, the *SEforALL* goal of universal electricity access.

With the *Social Planner's perspective*, we conduct a stylized welfare assessment of a subsidization policy. We find that the benefits internalized by solar kit buyers, as reflected in their WTP, do not cover the costs of off-grid solar electrification. Full subsidization would hence leave an *internal return on investment gap* (referred to as 'social surplus loss' by Lee et al. (2019)). From a welfare perspective, a full subsidization would only be justified if non-internalized benefits, i.e., external effects and long-term or unknown private benefits that are not reflected in the WTP, are high enough to close this gap. If non-internalized benefits do not close this gap, the welfare effect of a subsidization would be negative.

The gaps range between 9 and 116 USD per household for our three different technologies, and even when we account for a potential upward bias in our bids from declining and defaulting, the gaps are smaller than what Lee et al. (2019) observe for on-grid electrification. This is simply due to the considerably lower costs of off-grid electrification. To ponder whether a full subsidization policy for solar is more justifiable than for grid extension, in a next step, we provide a review of the growing rigorous literature studying both internalized and non-internalized benefits of electrification. The evidence suggests the effects of small off-grid solar are generally positive, but there is no indication of an effect on transformative economic development. Compared to on-grid electrification, non-internalized benefits of off-grid solar are certainly lower in absolute terms. In relative terms, though, they likely close a large part of the *internal return on investment gap* given the high costs of grid extension. We therefore conclude that, if mass electrification is a political goal, off-grid solar is the preferable technology to reach much of Africa's rural poor.

1.2 Background

1.2.1 Policy background

For many African governments, grid extension is the default intervention to increase access to electricity and to reach the SDGs and the SEforALL goal. In recent years, though, decentralized solar technologies have gained prominence as a lower-cost alternative, in particular because production costs of panels, storage systems, and LED lights have decreased considerably. Since 2009, the World Bank programme *Lighting Global* has supported the international off-grid lighting market for products of up to 10 Watts. The so-called pico-solar products promoted by the programme provide varying basic energy services depending on the panel size, such as lighting, radio, and mobile phone charging. Larger off-grid solar products, typically referred to as solar home systems (SHS), are additionally able to power TV sets and comparable devices, but not high-wattage devices (e.g., fridges) and appliances that run on alternating current.

In the absence of electricity, people in rural Sub-Saharan Africa (SSA) light their homes using traditional lighting sources – kerosene-driven wick and hurricane lamps or candles. In recent years, dry cell battery-powered LED lamps have become widely available in rural shops and are increasingly used (see Bensch et al. 2017). In the absence of any external support from governments or international programs, the better-off stratum in rural Africa uses mostly non-branded solar kits and products (Bensch et al. 2018, Grimm and Peters 2016, Lighting Global

2016).³ Very poor households in rural areas resort to only the dim light emitted by the cooking fire. For many households, spending on kerosene and batteries constitutes a considerable part of their total expenditures. This level of baseline lighting consumption is an important factor for a household's decision to invest in a solar kit, since the replacement of traditional energy expenditures alter cash flow expectations.

Lighting Global's approach assumes that branded off-grid solar products will make their way into households through the market. The programme has introduced a quality verification system and supports manufacturers and retailers in overcoming information asymmetries that might prevent customers from buying the products. Credit constraints are eased via credit and smart payment systems such as PAYG, which allows customers to pay for the kit in small instalments, often via mobile money. An additional innovative feature that can be combined with PAYG is to lock the solar kit remotely in case of non-payment through an installed microchip connected to a mobile phone network (Yadav et al. 2019). Generally, Lighting Global opposes direct end-user subsidies. According to Lighting Global (2016), around 4.3 million pico-solar kits were sold in Africa, with sales concentrating in Ethiopia, Kenya, and Tanzania. So far, customers are mostly better-off households.

SEforALL has established a multi-tier system within the so-called Global Tracking Framework (SEforALL 2013), which defines what type of electricity supply qualifies as modern energy. For example, a regular connection to the national grid qualifies as Tier 3 or 4, because it provides sufficient power for lighting, a television, and a fan all day. A SHS qualifies as Tier 1 or 2 depending on its capacity. Tier 1 electrification is defined as access to electricity with a peak capacity of at least 1 Watt, and access to basic energy services, including a task light and a charger for radios or phones. Service qualities and costs of the different tier technologies vary considerably. The retail price of the smallest pico-solar kit used in this study is 13 USD.⁴ For comparison, the World Bank (2009) estimates a cost range for on-grid electrification in rural areas of 730 to 1450 USD per connection, which is confirmed by Lee et al. (2019) for the case of Kenya, by Lenz et al. (2017) for Rwanda, and Trotter et al. (2019) for Uganda. In Chaplin et al. (2017), connection costs are as high as 6,600 USD per household because of low population density and low connection rates in their study area in Tanzania.

³ We use "branded" products to refer to solar kits that are quality verified by Lighting Global.

⁴ We use the official exchange rate in April 2016 for conversion, i.e., 100 Rwandan Franc (RWF) = 0.13 USD.

1.2.2 Country background

The Government of Rwanda strongly prioritizes electrification to reach its poverty reduction goals (MININFRA 2016 and 2018). It is the government's objective to increase the household electrification rate to 100 percent by 2024, of which 48 percent are expected to be connected via decentralized energy solutions. The country's Electricity Access Roll-Out Program (EARP) increased the national connection rate from six to 35 percent between 2009 and 2017, of which 11 percent have access to off-grid solutions (MININFRA 2018). More recently, the so-called *Bye Bye Agatadowa* initiative has attracted some attention with its aim of eliminating kerosene lamps completely from the country by facilitating access to pico-solar products. In the African context, this engagement of the government in expanding energy access is unprecedented. It is important to note that the communities sampled for this study at the time of the experiment had not been reached by these activities and no concrete plan for electricity-related roll-out had been announced for the near future. In that respect, they resemble typical off-grid areas in Africa (see Section 1.3.1).

1.3 Research approach and data




We conducted a randomized controlled trial (RCT) among 323 randomly selected households in 16 rural communities in Rwanda and elicited the WTP for three different solar kits using a real-purchase bidding game based on the BDM mechanism. A team of one field coordinator and five to seven enumerators visited one community per survey day. One enumerator visited each household individually to offer the three solar kits and conduct the interview. Furthermore, we randomly allocated three different payment periods to households, either one week, six weeks, or five months. To prevent fraud at the enumerator level, we implemented the randomization by randomly assigning one of the three payment periods to each enumerator in the morning of each survey day. The randomization of payment periods is thus stratified at the community level. In this section, we briefly describe the three solar technologies that were offered, followed by the sampling process and the bidding game to elicit the WTP.

1.3.1 Off-grid technologies offered in experiment

We cooperated with *Dassy Enterprise*, a Kigali based vendor of solar products, and selected three kits out of the portfolio. Table 1.1 presents these three devices in greater detail. The most basic kit is the *d.light S2* ("Kit 1"), an LED lamp with a small, integrated solar panel. It only provides lighting and thus does not reach Tier 1 according to the SEforALL multi-tier metric. The second kit offered is the *Sun King Pro 2* ("Kit 2"), which is eligible for Tier 1 because it

provides lighting and phone or radio charging via two USB ports. Kits 1 and 2 are portable and can be used as a desk lamp or attached to a wall or ceiling. Both kits are similar to other (borderline) Tier 1 pico-solar kits available on the Rwandan market and elsewhere in Africa (Lighting Global 2016). The third kit offered, the *ASE 20W Solar DC Lighting Kit* (“Kit 3”), is a SHS, i.e., the solar panel is installed outside and charges a separate battery, which in turn is connected to four LED lamps and a charging station with six USB ports. Kit 3 and its 20 W panel still qualify as Tier 1. It is small compared to other SHS systems available on the market, but it comes close to Tier 2 in terms of the variety of electricity services it offers.

Table 1.1: Specifications of solar technologies

	Kit 1	Kit 2	Kit 3
			
Model	d.light Design S 2	Greenlight Planet Inc. Sun King Pro 2	ASE 20W Solar DC Lighting Kit
Kit type ¹	Plug-and-play	Plug-and-play	Component based
Full battery run time ² (in hours)	6.5	5.9 - 13.1 ³	4 – 36 ⁴
Total light output (in lumens)	25	81 – 160 ²	220
Panel size (in Watts)	0.5	3.3	20
Features	1 LED lamp	1 LED lamp, 2 USB ports, 3 brightness settings	4 LED lamps, 6 USB ports, Separate battery of 14Ah
<i>SEforALL</i> multi-tier classification	Tier 0	Tier 1	Tier 1
Approximate market price in Rwanda (in USD)	13	37	180
Life span ⁵ (in years)	3	6	4

¹ ‘Plug-and-play’ refers to all-in-one packaged kits, ‘component based’ to devices in which panels, batteries and appliances are compiled independently (see Lighting Global 2018); ²run time estimates do not include mobile phone charging; ³depending on the brightness setting; ⁴depending on the number of lamps in use. ⁵According to Dassy Enterprise’s manufacturer specification; Sources: <https://www.lightingglobal.org>, Dassy Enterprise Rwanda; Pictures: Brian Safari, IB&C.

The Rwandan market prices of the three kits range between 13 USD for Kit 1 and 180 USD for Kit 3. According to *Dassy Enterprise*, the expected lifetime is three years for Kit 1, six years

for Kit 2 and four years for Kit 3. Note that these estimates are generally conservative, especially for Kit 3. In general, the lifetime of comparable SHS is on the order of eight to 12 years, but depends on usage patterns and intensity, replacement of components, cleaning of the panel, and environmental conditions (temperature, wind, dust, and humidity).

1.3.2 Sampling

We used a two-stage sampling approach on the community and the household level. We selected communities that resemble typical target regions of solar technologies and used four selection criteria:

- (i) Communities are not foreseen to be connected to the grid in the near future.
- (ii) Areas exhibit appropriate solar radiation levels (see Figure 1.1).
- (iii) Communities are not exposed to systematic marketing activities of solar product companies, and comparable products are not widely available in the villages or nearby villages. This reduces the risk of preconceived price ideas, which could lead to strategic bidding in our bidding game. As explained in more detail below, though, it is impossible to completely preclude households from having access to off-grid solar via charities or relatives and friends in urban areas.
- (iv) Communities are not adjacent to prevent communication between survey participants from different communities.

The two-stage sampling process consisted of non-random community selection, and subsequent random household sampling. First, we obtained a list of communities (so-called imudugudu) from the Rwandan government that all met the criteria outlined above and verified the government's assessment via phone with local authorities at the cell level.⁵ Based on these criteria, we compiled a list of eligible communities and then drew 16, distributed across 11 sectors in three out of five Rwandan provinces (see Figure 1.1). In a second step, we chose 323 households through simple random sampling⁶ at the community level on the day of the field visits. For logistical reasons, the numbers of interviews per village varies and the sample is not

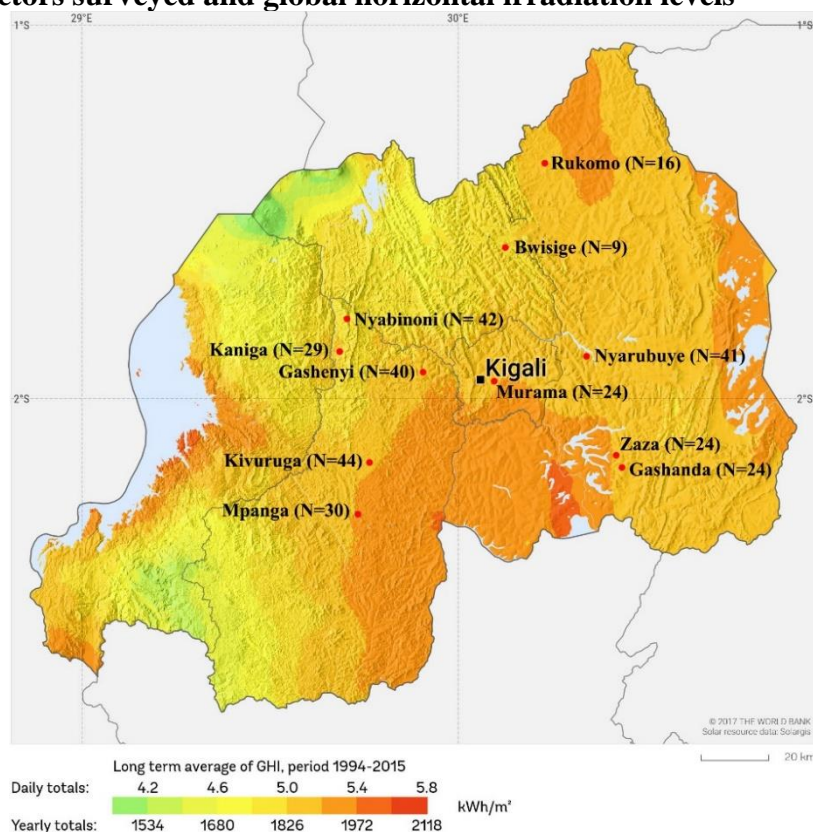
⁵ Rwanda is divided into five administrative levels, including provinces, districts, sectors, cells, and imudugudu. 416 sectors cover 2,148 cells, of which each covers on average seven imudugudu (see National Institute of Rwanda 2008).

⁶ More specifically, we applied random walk sampling. Interviewers were assigned the different community paths and were instructed to interview every X^{th} household on their path(s). In case of absence, the next neighbor, i.e., house $X+1$, was interviewed. X was calculated dividing the community population size by the expected number of interviews.

equally distributed across communities and sectors (see Figure 1.1). Households could not self-select into participation.

The selection procedure resulted in communities with an average size of 178 households and 847 people. The communities are quite remote, located an average of 14 km from the nearest main road, which is a considerable distance for mountainous Rwanda. Public infrastructure is available only in a few communities; this includes primary schools (in five communities), health centers (in one community), and weekly markets (in five communities). Only two of 14 interviewed community chiefs expect their communities to be connected to the national electricity grid soon.

Figure 1.1: Sectors surveyed and global horizontal irradiation levels



Note: We indicate the sectors surveyed, which contain between one and two surveyed communities. The sample size surveyed per sector is in parentheses. Source: Own illustration; map obtained from the Global Solar Atlas⁷.

In line with our selection criteria, communities are not exposed to systematic promotion of solar products. Off-grid solar products comparable to Kit 1 and Kit 2 are not available in local shops. Only around half of the communities had some exposure to NGO-led marketing activities of larger SHS. As we show later, the technology is not completely new to the population, but

⁷ The Global Solar Atlas 2.0 is a free, web-based application, developed and operated by the company Solargis s.r.o. on behalf of the World Bank Group, utilizing Solargis data, with funding provided by the Energy Sector Management Assistance Program (ESMAP). For additional information: <https://globalsolaratlas.info>.

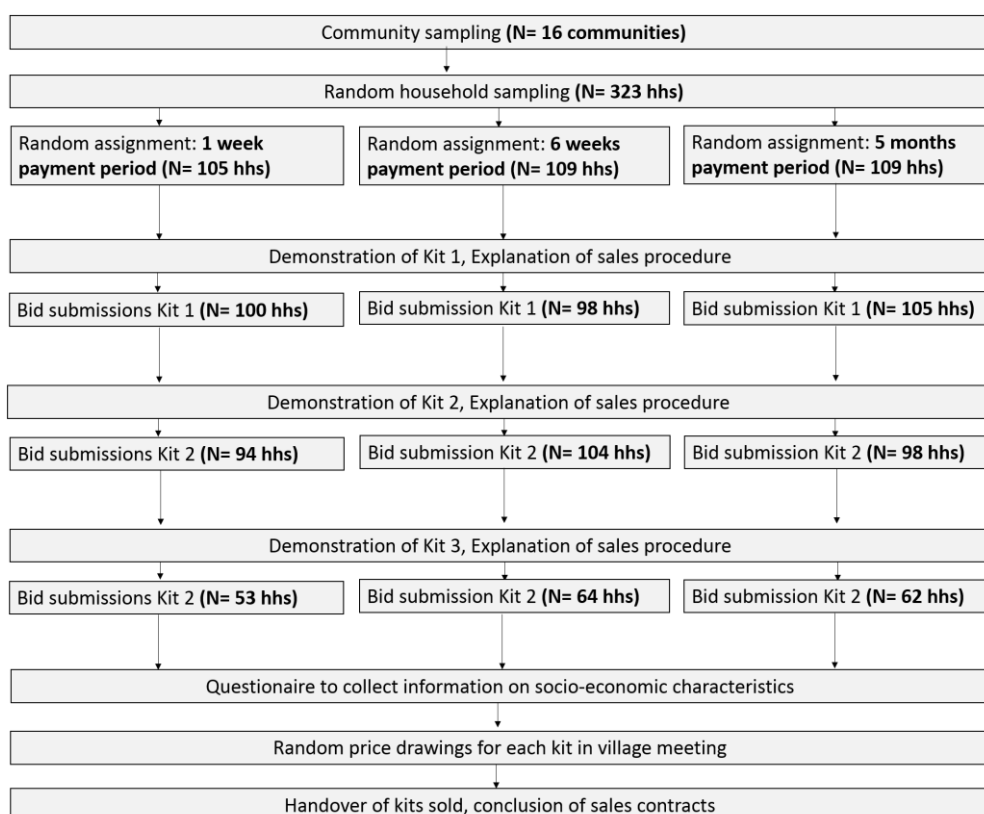
ownership rates of solar kits at the time of study were low with 29 out of 323 households currently using one, and another 15 households that had been using one that was not operational anymore. Prices of solar kits were in general unknown to the population (see Section 1.4.1.).

1.3.3 Survey implementation and the real-purchase bidding game

The survey was implemented between August and November 2015 in cooperation with *Inclusive Business and Consultancy (IB&C)*, a Kigali-based consultancy, *Rwanda Energy Group (REG)*, Rwanda's public energy agency, and *Dassy Enterprise*.

For the household interviews, the financial decision maker was called and informed that we would sell a solar kit following a sales procedure different from what is usually known on the market. Please see Appendix 1A for the experiment instructions used in the field. All households were asked for their consent to be interviewed and to participate in the bidding game but were not informed about the study's purpose or the randomization of the payment periods. Hence, typical survey effects might occur, but Hawthorne effects are unlikely. Enumerators worked in parallel within one community to avoid communication between participating households. Figure 1.2 presents the participant flow highlighting the sequential bidding game procedure in the field.

Figure 1.2: Participant Flow



Source: Own illustration.

The enumerators demonstrated the three solar kits to each household consecutively and offered the opportunity to bid for each one using the auction procedure described below. The process started with Kit 1, followed by Kit 2, and lastly Kit 3. When Kit 1 was offered, the households were not yet aware of the Kit 2 and 3 offers. Before Kit 2 was offered, the participants were told that they can only purchase one kit and were asked to decide which kit they would buy in case they make successful bids for both. Likewise, before Kit 3 was offered, participants were asked to decide which kit they would buy in case of two or three successful bids.⁸

The enumerators followed the same procedure for each kit. First, they demonstrated the kit. The enumerators had been trained beforehand by *Dassy Enterprise* to convey the key product information. Kit 1 and Kit 2 were demonstrated during the interview, while Kit 3 was too heavy to be taken to each household and was therefore only described in detail. Second, enumerators explained the BDM real-purchase bidding game procedure. Respondents were instructed that they could purchase the product only if their bid exceeded or equaled the randomly drawn price. The price to be paid was the randomly drawn price, not the bid. In each village, this price would be drawn in public in the afternoon. Moreover, it was explained that the households would not be allowed to purchase the product if their bids fell below the randomly selected price and that changing the bids afterward was not possible. It was emphasized that the price was not negotiable, and it could not be influenced in any manner by the enumerators or the households. Third, the randomly assigned payment period (one week, six weeks, or five months) was announced. The interviewed households were then offered the solar kit and asked for the highest price they would be willing and able to pay.

We opted for the BDM approach, because, unlike stated WTP approaches, it incentivizes truthful responses (see Berry et al. 2020). If the bidders overstated their real reservation prices, they would have to buy the product at a price higher than their actual valuations. In contrast, by understating their real reservation prices, they might miss a purchase opportunity at a price that was less than or equal to their valuations. Another useful feature of BDM is that it allows for observing exact point-of-purchase prices, i.e., it allows for drawing a detailed demand curve. It therefore yields more precise, higher-resolution data on households' WTP as compared to take-

⁸ This procedure ensures independence between bids. A downward bias due to bid dependence is very unlikely for two reasons. First, households were not aware of the Kit 2 (or 3) offer when bidding for Kit 1 (or 2). Second, the capacity of the kits presented increases consecutively. A potential upward bias may still arise if households increased their bid more than they increased their actual valuation because they reasoned that the superior kit introduced next should have a higher price than the one formerly presented. However, theoretically, incentive compatibility of the BDM approach should prevent this. Note that only five households made inconsistent bids, i.e., higher bids were made for a smaller kit than for a larger one.

it-or-leave-it approaches, which provide only WTP bounds. Furthermore, compared to a Vickrey second-price auction, the BDM set-up prevents collusion or conflict between different bidders during the bidding process, because they do not bid against each other, but against a random price draw.⁹ However, the BDM method is sometimes criticized for its complexity. In particular, in poor rural settings, the participants' comprehension of the bidding procedure can hinder its success. Therefore, before we offered the solar kits, we conducted a test round with a hypothetical auction for a mobile phone.

The households were informed that *Dassy Enterprise's* field services would provide a one-year warranty. In this rural Rwandan context, warranties are uncommon and signal good quality. The instructions the enumerators presented to the participants before the game also contained some soft marketing messages. The key features of the three kits were introduced, including the different electricity services they would allow for. Participating households were informed about average spending of rural Rwandan households on batteries, kerosene, and candles, i.e., those sources that can be replaced by the solar kit, using the information we collected during earlier surveys (see Lenz et al. 2017). We administered our socio-economic questionnaire only *after* the bidding processes for the three kits, to avoid distorting effects on the participants' mind-set and bidding behavior.

Moreover, the participants were informed about the minimum and maximum prices in the draw. The lower bounds of these ranges were set at a very low price level of approximately 30 percent of the market prices for Kit 1 and Kit 2 and at 64 percent of the Kit 3 market price.¹⁰ The upper price bounds were the Rwandan market prices of the respective solar kit. The price range was disclosed to the participants because, during preparatory field visits, we noticed that most households have little knowledge about actual prices and found that an entirely non-anchored WTP might even discourage participation.¹¹ We chose this upper bound to be sufficiently high to cover the participants' maximum WTP (which turned out to be true, see next section). The participants were simply informed once about the price ranges, without any further appeal to bid within this range.

⁹ See Berry et al. (2020) for a profound discussion of BDM. Yet, one might suspect that the door-to-door marketing approach and the lottery feature of the BDM method increase the attention potential customers dedicate to the product, which could increase the WTP compared to a real-world market setting (see Bensch and Peters 2019 for a discussion).

¹⁰ The price range was between 4 USD and 13 USD for Kit 1, 13 USD and 37 USD for Kit 2, and 116 USD and 180 USD for Kit 3.

¹¹ Answering a non-anchored WTP question can be cognitively very challenging (Kaas and Ruprecht 2006), particularly when participants are confronted with an unknown product.

After the household visits were completed, the random price draw for each solar kit was done openly in an afternoon community meeting in the presence of participants (97 percent were present). We decided to draw prices at the community level (i.e., one price per kit and community) instead of the household level, in order to avoid social tensions induced by different prices within the same community.

Those participants whose bids exceeded the drawn price received the product the same day and signed a binding sales contract. The contract specified payment modalities and the deadline until when the full price had to be paid. No specific sanctions in case of non-payment were announced. Participants were offered the possibility to make a voluntary advance payment. Remaining payments could be made in instalments via mobile banking through one of the three Rwandan mobile phone operators.¹² We started reminder calls after the deadlines of the respective payment period and announced we would take back the kits in case of non-payment. At the time of survey implementation, *Dassy Enterprise* and other Rwandan small solar kit providers did not offer payment schemes featuring remote monitoring to shut down the solar kit (see Sections 1.2.1. and 1.5.2.). All but two households were sufficiently familiar with mobile banking services. These two households had already opted out of the game during the interview.

We encountered two challenges when implementing the bidding game: First, 28 households (15 percent) effectively did not sign a purchase contract even though they won the bidding game (henceforth: ‘decliner’). Second, about a third of successful bidders in our experiment did not make the full payment (henceforth: ‘defaulter’). We perform comprehensive robustness checks and discuss possible biases for our results in Section 1.6.

1.4 Results

1.4.1 Summary statistics and balancing test

Table 1.2 summarizes the key socio-economic characteristics of our sample and tests whether the randomized payment period groups are balanced. While the three groups are generally well balanced, the multiple *t*-tests show that the groups differ in more aspects than expected by chance. The magnitude of statistically significant differences is small for most variables, but differences in monthly expenditures are surprisingly notable, which might bias our assessment of the payment period’s effect. We therefore control for all variables when evaluating the effect

¹² The payment conditions were explicitly explained before conducting the BDM game.

of payment periods on the WTP and briefly explore whether our findings are sensitive to bias induced by the imbalance. Our findings are not affected (see Section 1.4.3), and we have no indication of an incorrect implementation of the randomization.

To get a sense of the amortization periods for the three solar kits, in Appendix 1E we present their market prices in relation to the total energy expenditures that they can replace (for example, Kit 1 can only replace lighting and not phone charging expenditures). These estimates suggest that the amortization periods for the three kits are on average 30, 37, and 144 months, reflecting the low baseline energy expenditures of the average rural household.¹³

Table 1.2: Descriptive statistics and balancing test for randomized payment periods

	Mean			p-value		
	Period 1	Period 2	Period 3	Period 1 vs. 2	Period 1 vs. 3	Period 2 vs. 3
<i>Socio-economic characteristics</i>						
Female respondent/bidder	0.44	0.37	0.44	0.29	0.99	0.28
Head of household's years of education	4.44	4.12	4.75	0.45	0.51	0.17
Household size	4.43	4.81	4.33	0.11	0.66	0.04**
Head of household is a farmer	0.78	0.81	0.81	0.63	0.56	0.91
Share of students in household	28.66	38.19	30.63	0.01***	0.59	0.03**
House with tile roofing	0.24	0.22	0.17	0.74	0.21	0.34
Monthly non-energy expenditures [#]	48.20	66.08	61.17	0.02**	0.11	0.57
<i>Baseline energy consumption</i>						
Monthly phone charging expenditures [#]	1.04	1.11	1.16	0.64	0.48	0.76
Monthly energy expenditures ^{#,§}	1.37	1.85	1.57	0.11	0.41	0.38
Owns rechargeable lamp	0.08	0.06	0.10	0.67	0.50	0.26
Owns car battery	0.00	0.04	0.03	0.03**	0.08*	0.53
Owns solar kit	0.07	0.12	0.08	0.23	0.63	0.46
N	104	113	106	217	210	219

*Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ denote statistical significance. Expenditures are in USD. [#] The values are bottom and top coded at 2 percent and 98 percent of the distribution respectively to eliminate outliers. [§] Including expenditures on kerosene, dry-cell batteries, and candles; we excluded expenditures for charcoal and firewood, since the services for which these fuels are used (cooking, ironing) are not replaceable by solar kits; for those 26 households that own a rechargeable lamp, we did not elicit expenditures for recharging the lamp.*

Around 11 percent of our sample (36 households) already possessed a modern, functioning electricity source at baseline, which were mostly solar kits (29 households). Most of the solar kit owners (67 percent) received their kit from urban areas, presumably from friends or relatives, and 20 percent obtained them from charities. The bid submitted by households that already own a modern electricity source, *i.e.*, a solar kit or car battery, cannot be compared to

¹³ The amortization period decreases (increases) considerably for households with expenditures higher (lower) than the average; see Section 1.5.1. Also note that these monetary savings do not capture costs and utility that could be derived from cheaper energy and additional services, especially for Kit 3.

the one submitted by households who bid for their first source. We later explore the robustness of our findings to the exclusion of these households.¹⁴

Information about solar kit prices was very limited in the surveyed communities at the time of the survey. We asked participants after the bidding game to gauge the market prices of the three kits. Only four out of 44 participants (29 currently and 15 formerly owning a kit) were able to name a price, confirming that most of the solar kit-owning households received them at no cost. Among the 86 percent of survey participants that had never possessed a solar kit, only 10 respondents said they had an idea of the market price.

1.4.2 Revealed WTP in bidding game

Most visited households agreed to participate in at least one of the three bidding games. As demonstrated in Table 1.3, the highest share of non-bidders is observed for Kit 3 (45 percent), whereas it is clearly below 10 percent for Kit 1 and 2. The dominating reason for non-bidding is that households noticed that they were not able to make a bid above the lower bound (recall that the range for the randomly determined prices was disclosed before the game).¹⁵ In order to avoid a selection bias due to a partly censored sample, we estimate the synthetic WTP also for those who opted out using an interval regression (IR) model.¹⁶

Table 1.3 depicts the results of the bidding game, not yet accounting for the different payment schemes. We show both the WTP of those households that made a bid, and the corrected WTP of the full sample using the IR model which controls for all household variables from Table 1.2, community fixed effects and timing of survey visit. Throughout the chapter, we report IR-corrected median WTP, and as shown in Table 3, IR-corrected mean WTP values hardly differ.

The median bid for Kit 1 across all treatment groups was roughly 4 USD, which is equivalent to 30 percent of the market price. The median price bid for Kit 2 was slightly more than 15

¹⁴ Regression results for the restricted sample can be found in the Appendix Table 1F.2. The mean WTP of the restricted sample is reported in Section 1.4.2.

¹⁵ More specifically, for Kit 1, most non-bidders opted out before making a bid because the Kit 1 does not fulfill their needs (mostly related to phone charging). Similarly, for Kit 2, almost half of the 27 non-bidders state that it would not fulfill their needs and eight non-bidders referred to a lack of financial resources. For Kit 3, almost all non-bidders stated they did not have the financial resources.

¹⁶ A regular Tobit model is unable to handle those households that made bids below the threshold (enumerators encouraged participants to submit a bid even if the WTP is below the lower bound). We therefore use the interval Tobit model (intreg), which is a generalization of the Tobit model that allows for defining censoring and interval ranges for each observation individually (see Cameron and Huppert 1989).

USD, covering 41 percent of the market price. For Kit 3, the median bid was roughly 64 USD, which covers 36 percent of the market price.^{17, 18}

In total, 182 households won the bidding game, i.e., at least one bid exceeded the randomly drawn price (74 households for Kit 1, 93 for Kit 2 and 15 for Kit 3). However, 28 of the 182 winning households (or 15 percent) did not proceed with the purchase.¹⁹ The majority of participants attended the price draw meeting and also stated to be satisfied with their bids *after* the price had been drawn. Only one percent was unsatisfied because of having bid too much and 14 percent of bidders were unsatisfied because they bid too little.²⁰

Table 1.3: Bidding game outcomes

	Kit 1		Kit 2		Kit 3	
Share making a bid	0.94		0.92		0.55	
Market price	12.88		37.35		180.32	
WTP: Bidders only						
Mean	4.92	(2.07)	16.85	(7.18)	93.68	(45.25)
Median	4.51		15.46		115.92	
WTP: Full sample (IR-corrected)						
Mean	4.82	(2.04)	16.34	(7.08)	77.43	(39.37)
Median	3.86		15.46		64.40	
WTP as share of monthly expenditures ^{#,§}						
Mean	20.53	(28.81)	64.15	(88.07)	381.49	(842.81)
Median	11.90		37.91		186.22	
WTP as share of monthly expenditures ^{#,§} (IR-corrected)						
Mean	20.62	(31.21)	65.82	(94.71)	330.85	(673.12)
Median	11.61		37.45		177.42	
N wins in experiment	74		93		15	
N effectively bought (N of decliners)	59	(15)	85	(8)	10	(5)
N	323		323		323	

Note: We display standard deviations in parentheses. Values are in USD. [#]Values are bottom and top coded at two percent and 98 percent of the distribution respectively to eliminate the effect of outliers. [§]Excluding expenditures on wood and rechargeable lamps. IR-corrected values are predicted using an Interval Regression model using all variables listed in Table 1.2.

Figure 1.3 uses the households' WTP to illustrate the demand curves for the three kits. The figure shows that the end-user prices at which 98 percent uptake²¹ would take place in our

¹⁷ Excluding the households that already possessed a solar kit or a car battery prior to the experiment has little impact on the results (no change of mean values for Kit 1, 0.32 USD higher for Kit 2, and 0.42 USD higher for Kit 3; median values do not change for any kit).

¹⁸ The corresponding WTP in the Lee et al. (2019) study is around 147 USD that is elicited using a take-it-or-leave-it approach. While the authors do not analyze the average WTP across the sample, the value corresponding to our average WTP can be obtained by dividing the fitted consumer surplus of 12,421 USD by the average community population of 84.7 households.

¹⁹ In Section 1.6, we test the implications of decliners for our findings.

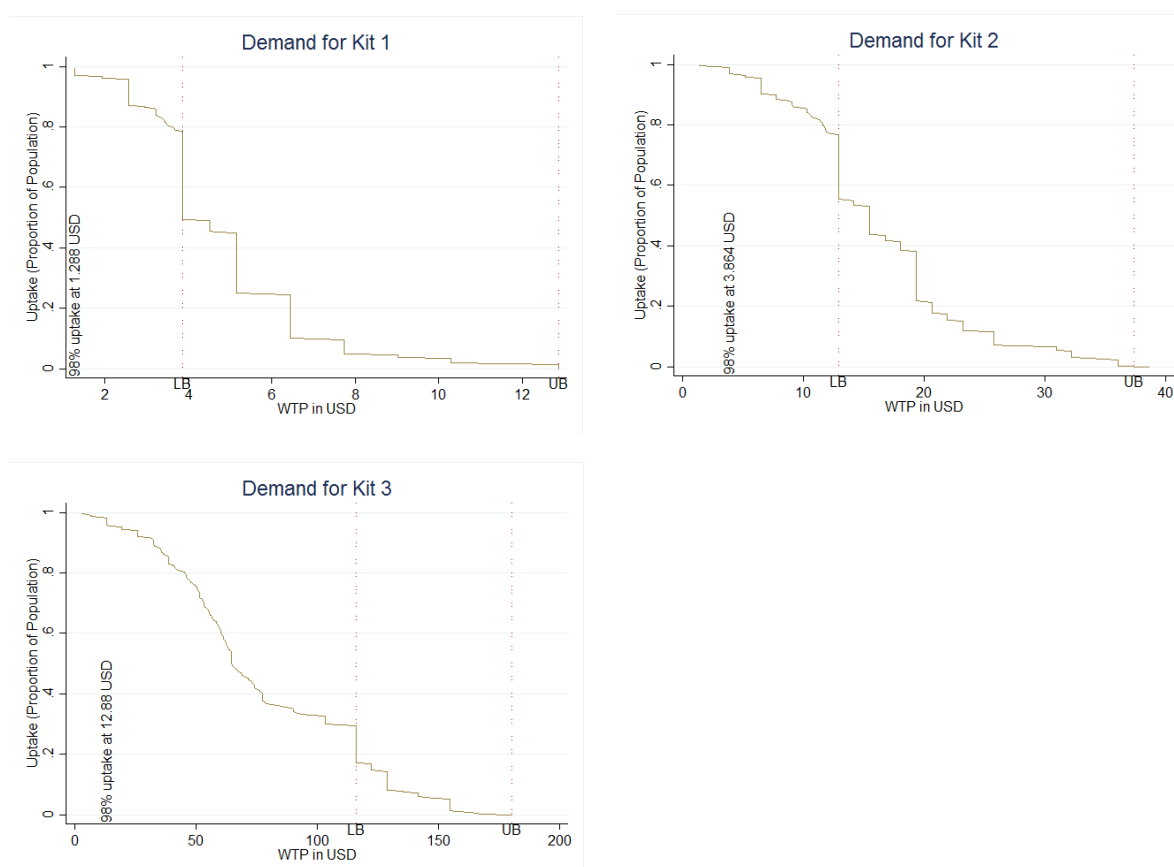
²⁰ These bidders either bid below their valuation during the bidding game, or their valuation changed after the game, for example due to envy or social comparison during the public price drawing in their community.

²¹ The remaining two percent made bids close to zero.

sample amount to less than 11 percent of the kits' market prices, namely 1 USD for Kit 1, 4 USD for Kit 2, and 13 USD for Kit 3.

The distribution of bids displayed in Figure 1.3 suggests an anchoring effect due to the announcement of price ranges, in that the observable bids cumulate above the lower price bound for all three kits. Two distortive effects can lead to this bidding behavior. First, bids could be biased downwards if participants gamble to get the kit at the lowest price. Second, bids could be biased upwards if participants with a real WTP slightly below the lower bound are tempted to adapt it to this lower bound. Even if we – conservatively – assume the estimates to be slightly biased downwards, it seems safe to conclude that the true WTP is clearly below the market price. Only few observations (five for Kit 1, one for Kit 2, two for Kit 3) reach this upper bound.

Figure 1.3: Demand for solar kits



Note: LB and UB indicate the lower and upper price bounds. The demand curves depict individual bids of households. For households that opted out of the bidding, we estimate values via an IR estimation.

Comparing the bids to the households' total expenditures reveals the priority that modern lighting has for people in rural areas (see Table 1.3). While the median household is already willing to pay almost 12 percent of its monthly expenditures for Kit 1, the increase of bids when

phone charging services are added is especially striking.²² For Kit 2, the median household is willing to pay 37 percent of the total monthly expenditures. For Kit 3, the median share corresponds to 177 percent of the bidders' monthly expenditures. If we look at mean values, the shares are even substantially higher at 21, 66, and 331 percent for Kit 1, Kit 2, and Kit 3, respectively.

1.4.3 Effect of relaxing liquidity constraints

In this section, we examine the causal effect of relaxing liquidity constraints on the bidders' WTP. We regress the bidders' WTP for each of the three solar kits in a log-linear model on the randomized payment scheme in three different control variable specifications. We account for the censored samples again by using the IR model. For all three specifications, we include community fixed effects and control for the date of the bidding game. The latter might play a role because the survey work was spread across three months and the later interviews were closer to Rwanda's second harvest period in December. The main results are shown in Table 4, and comprehensive regression results including control variables can be found in Appendix Table 1F.1. Specifications II and III consecutively include two sets of control variables, socio-economic characteristics, and baseline energy consumption variables. The latter might be endogenous to the reported WTP, but they could also be important covariates to account for imbalances diagnosed in Table 1.2 and to increase precision. For example, phone charging expenditures are significantly correlated with the WTP for Kit 2 (which has a charging port) but not with the WTP for Kit 1 (which has no port).

The effects of relaxing liquidity constraints are very consistent across the three kits. Offering a six-week payment period instead of a seven-day payment period for most specifications increases the WTP, but the increase is very small in size and not statistically significant. For all three kits, the five-month treatment increases the WTP by four to 13 percent. Statistically significant increases of a five-month payment period are only observed for Kit 1. More specifically, the mean WTP of participants with a one-week payment scheme of 5 USD (also see Table 4) increases by 12 percent when a five-month payment period is granted.

Yet, this increase must be understood in the context of interest rates on local formal and informal capital markets. Savings and Credit Cooperative Organizations (SACCOs), which

²² The underling variable is generated by dividing the households' individual bid by the households' individual total expenditures. If we divide the median (mean) WTP by the median (mean) household expenditure, the shares amount to 10 percent (8 percent) for Kit 1, 40 percent (25 percent) for Kit 2, and 166 percent (120 percent) for Kit 3.

provide the most accessible formal source of financing in rural Rwanda, offer credit at interest rates of 2.5 to 5 percent monthly (AFR, AMIR and MicroFinanza Rating 2015). When we apply this interest rate to our zero-interest rate payment periods, the positive treatment effect on the WTP vanishes.

Table 1.4: Payment periods and WTP

	Kit 1			Kit 2			Kit 3		
	I	II	III	I	II	III	I	II	III
Six weeks	0.022 (0.698)	0.009 (0.868)	0.014 (0.808)	0.016 (0.821)	-0.008 (0.911)	-0.009 (0.898)	0.108 (0.415)	0.088 (0.499)	0.058 (0.649)
Five months	0.127 (0.024)**	0.128 (0.025)**	0.120 (0.037)**	0.087 (0.214)	0.090 (0.193)	0.070 (0.298)	0.075 (0.560)	0.073 (0.574)	0.042 (0.743)
N	323	323	323	323	323	323	323	323	323
Mean WTP of one-week payment group (in USD)	4.50	4.50	4.51	15.46	15.43	15.44	70.87	70.58	77.67
<i>Control variables</i>									
Community and date	YES	YES	YES	YES	YES	YES	YES	YES	YES
Socio-economic characteristics	NO	YES	YES	NO	YES	YES	NO	YES	YES
Baseline lighting consumption	NO	NO	YES	NO	NO	YES	NO	NO	YES

Note: We display coefficients from an IR estimation with robust standard errors. The dependent variable is log of WTP. The base category is a one-week payment period. See Table 1F.1 for full regression results including control variables. Furthermore, Table 1F.2 shows results for the sample excluding households with a modern electricity source at baseline.

In sum, according to these findings, relaxing liquidity constraints is not the panacea to make off-grid solar affordable for the rural poor.²³ Note that one important caveat for the strict interpretation of payment periods are the decliners and defaulters. We discuss in detail the implications of these two groups for our findings in Section 1.6.

1.5 Interpretation of Results

In this section, we interpret our findings from two perspectives. First, in the *SEforALL perspective*, we discuss the implications of our results for the market-based approach currently favored by the SEforALL initiative and pursued by many governmental interventions. Second, in the *Social Planner's perspective*, we provide a stylized cost-benefit analysis of a full subsidization policy.

²³ Note that the slight imbalances between groups diagnosed in Section 1.4.1 do not affect this qualitative finding. First, we control for those differences in Specification II and III, and second, somewhat better-off households benefited from being assigned longer payment periods (see Table 1.2). Thus, similar to the discussion in Ben Yishay et al. (2017), we would expect the imbalance to bias our results in favor of finding effects of extended payment periods.

1.5.1 The Sustainable Energy for All perspective

Households in our survey areas have a WTP that covers much less than half of the current market prices. It will hence be difficult to reach the very poor, and thus achieve universal access, with a solely market-driven approach. At the same time, as our analysis has shown, households reveal a high relative valuation of off-grid solar compared to their expenditure levels. Qualitative statements in semi-structured interviews confirmed the importance of electricity for households, even if provided by off-grid solar rather than by grid connection.

Providing extended payment periods does not eliminate the affordability barrier. However, the payment schemes we offered are potentially not long enough, especially for Kit 3. Poor households might be particularly interested in payment schemes that enable them to make the investment without changing their cash flow over time, which would require the investment to amortize within the payment period. The amortization periods that enable households to invest in off-grid solar without changing their cash flow are at 30 months, 37 months, and 144 months for Kit 1, 2, and 3, respectively (see Appendix 1E for calculations). Such payment periods are probably unrealistic in real-world loans, also, as Lighting Global cautions, because “extending PAYG payment period[s] too far in an attempt to engineer affordability” increases the likelihood that “consumers become unwilling to continue to make payments” (Lighting Global 2018, p.131). Moreover, extending payment periods further also increases transaction costs and, hence, interest rates.

Furthermore, it is crucial for the *SEforALL* perspective that this amortization period is heterogeneous across the expenditure distribution. This is because replaceable energy expenditures (mostly on kerosene and dry-cell batteries) vary considerably. Looking at the quintile with the highest energy expenditures replaceable by the kits, the period decreases to 7, 9, and 35 months. This reduction is considerable and hints at the success stories of *M-Kopa*, *BBOX* and *d.light*, which target the non-poor rural and peri-urban strata (Muchunku et al. 2018).²⁴ For the poorest quintile, by contrast, the investment into the three devices pays off only after 36, 57 and 217 months. These considerations show that a purely market-driven approach is unlikely to reach broader sections of the population. While component costs can be expected to decrease further in the future, this will probably not alter our affordability conclusion.²⁵

²⁴ Yadav et al. (2019) summarize the PAYG offerings of *M-Kopa* and *BBOX*. Their schemes include a deposit between 9 and 60 USD and monthly payments between 15 and 30 USD for a period of one to three years, depending on panel sizes ranging between 8 and 50W.

²⁵ Lighting Global (2018) estimates that component costs for pico-solar kits will decrease by seven percent and for SHS by 39 percent from 2016 to 2022 (p. 49ff.)

It must be cautioned, though, that our WTP analysis took a static perspective. As solar kits diffuse into the communities, peer effects and social learning are likely to kick in (Foster and Rosenzweig 2010). To the extent that such learning effects increase WTP over time, market-based dissemination reaches larger parts of the rural population. Indeed, as our supplementary analysis in Appendix 1G indicates, participants reveal a higher (lower) WTP if they have heard about positive (negative) features of solar kits or had positive (negative) experiences themselves. Yet, we argue that while such learning effects will surely increase the WTP, the tight budget constraints of households in our survey region and in most parts of rural Africa will prevail. Nevertheless, individual and social learning are important determinants of adoption, and we acknowledge that our design does not allow for testing dynamics of WTP when learning changes. We would need an additional treatment arm granting a trial period to test and learn about solar kits, which was not possible due to a limited research budget.²⁶

1.5.2 The Social planner’s perspective: A stylized cost benefit-analysis

In this section, we qualitatively assess the social cost-effectiveness of a full subsidization policy that reduces the end-user price of solar kits to zero, using the evidence from the emerging literature on socio-economic impacts of off-grid solar. We contrast the cost of a full subsidization policy – approximated by the solar kits’ market prices – with the households’ WTP. Since the participants’ WTP only accounts for their internalized benefits, but not for external effects or long-term private benefits, we label the gap between cost and WTP the *internal return on investment gap*. For on-grid electrification in Kenya, Lee et al. (2019) estimate this gap to be between 593 USD and 935 USD per household.²⁷ The magnitude of these numbers already demonstrates that the gap, by definition, will be much smaller for off-grid solar even if the WTP for off-grid solar was zero, simply owing to the much lower costs of off-grid electrification.

In order to approximate the cost of a full subsidization programme, we use the prices charged by Rwandan last-mile distributors. It is plausible to assume that these prices cover all logistics and servicing network costs. We thereby abstract from additional administrative costs, but also from potential economies of scale.

²⁶ For the case of cookstoves, Levine et al. (2018) indeed find substantial positive effects on adoption in Uganda, while Urpelainen and Yoon (2017) and Yoon et al. (2016) do not confirm this for off-grid solar, using product demonstrations and trial periods in India. There is also a growing literature on social learning and networks that could be tested for off-grid solar in future research (see Beaman et al. 2018, Ben Yishay and Mobarak 2018).

²⁷ Lee et al. (2019) use the term ‘social surplus losses’.

Table 1.5: Cost and internalized benefits of off-grid electricity per household (in USD)

	Kit 1	Kit 2	Kit 3
Cost	12.88	37.35	180.32
Median internalized benefits (as reflected in WTP)	3.86	15.46	64.40
Internal return on investment gap	9.02	21.90	115.92

Note: Median IR-corrected WTP values are used, see Table 1.3.

Table 1.5 shows the cost and internalized benefits of off-grid solar electrification, as well as the resulting *internal return on investment gap* of 9 USD per household for Kit 1, 22 USD for Kit 2, and 116 USD for Kit 3.

So far, this calculation ignores replacement investments that are required after the lifespan of the solar kits. Yet, even when accounting for replacement investments, our overall conclusion holds. To illustrate this, we take a conservative lifetime estimate of at least three years for Kit 1, of six years for Kit 2, and of four years for Kit 3 (see Section 1.3.1.), and assume replacing the solar kits after the respective lifetimes over a 20-year period. Keeping replaceable energy expenditures and costs of solar kits constant, the median *internal return on investment gap* now accumulates to 60 USD for Kit 1, 73 USD for Kit 2, and 580 USD for Kit 3, and thus is (at least for Kit 1 and 2) still less than on-grid electrification. For Kit 3, the very modest lifetime provided by *Dassy* becomes noticeable in this calculation. Moreover, production costs of off-grid solar are constantly decreasing – according to Lighting Global (2018, p.49) by 39 percent from 2016 to 2022 – which will further reduce the total cost over 20 years.

In view of the affordability bottleneck outlined above, should the social planner hence invest in subsidizing the distribution of off-grid solar? Leaving the normative SEforALL goal aside, this would be the case as soon as the external effects and non-internalized private benefits are high enough to close the *internal return on investment gap*. Two types of effects are not covered in our WTP values. First, households do not account for external effects. These could be, for example, reductions in environmental damages from kerosene and battery use or positive spillovers to neighbors who may also benefit from lighting, radio, or phone charging. In the literature, there is no evidence of spillovers, but, with regards to environmental effects, solar light has been found to reduce non-rechargeable battery usage (Grimm et al. 2017, Stojanovski et al. 2017). In particular, quality-verified off-grid solar might be in a position to decrease e-waste in countries with poor waste management infrastructure (Grimm and Peters 2016 and

Bensch et al. 2017).²⁸ The impact on greenhouse gas emissions, in contrast, is probably small (Baurzhan and Jenkins 2016).

Second, households' WTP might not reflect private benefits from solar kit usage that are unknown or that materialize only in the very long run. These include improved security, cleaner air and the related reduction in health hazards, as well as improved studying and working conditions and their potential positive effects on future employment. Grimm et al. (2017) in Rwanda, Rom et al. (2016) in Kenya, and Samad et al. (2013) in India provide evidence for positive effects on productivity of housework activities, health, and study time of children.²⁹ The latter, however, does not necessarily translate into measurable improved educational or economic development outcomes, a notion that is also confirmed in Stojanovski et al. (2017). Aevarsdottir et al. (2017) find exceptionally pronounced impacts of off-grid solar in Tanzania. They not only observe effects on direct outcomes such as expenditures and phone charging, but also on labor supply and income. Focusing on educational outcomes and health, Kudo et al. (2017 and 2018) as well as Furukawa (2014) also observe that off-grid solar is indeed used for studying purposes. Yet, in their trials in Bangladesh and Uganda, this again does not translate into better school performance or a decrease in respiratory symptoms. Likewise, Stojanovski et al. (2018) do not observe any effect on educational outcomes in Zambia. Lam et al. (2018) show in a small effectiveness study that exposure to harmful pollutants decreases considerably if solar lamps replace kerosene.

Hence, overall, while impact findings are heterogeneous, the literature tends to agree that off-grid solar improves living conditions and thus welfare, but transformative effects on socio-economic development are less likely. Therefore, it remains unclear how a full subsidization of off-grid solar would stand up to a welfare cost-benefit analysis. Yet, if one subscribes to the normative SEforALL universal access goal to be achieved by 2030, subsidizing off-grid solar for mass electrification seems to be more desirable than grid extension. The reasons are that costs of solar electrification are so much lower and demand at the intensive margin in rural areas is far below what grid electricity can provide, such that even small external and non-internalized private benefits can cover a larger part of the *internal return on investment gap*.

²⁸ Calculating the comprehensive environmental balance for off-grid solar is non-trivial, since it heavily depends on the environmental cost of solar kit production as well as the battery content and disposal systems at production and consumption sites.

²⁹ See Lemaire (2018) for a broader systematic review of the literature that confirms the summary provided here.

1.6 Robustness of results: decliners and defaulters

Hitherto we have interpreted the bids submitted in the BDM as the revealed WTP. Yet, 15 percent of winners declined to buy the kit and 34 percent of buyers defaulted on payment, which both indicates that bids, and hence this interpretation, could be upward biased. Later in this section, we will scrutinize the robustness of our results using an approach that is similar to Ben Yishay et al. (2017).

Declining to purchase is most likely due to a miscalculation during the bidding game, i.e., participants overestimated their ability to pay. There is also indication that participants who did not win their *favorite* kit altered their WTP and therefore declined to purchase the kit they won (see Appendix 1B). For defaulting, there are three potential reasons: (i) another miscalculation of ability to pay, (ii) tricking, i.e., participants already decided to default during the bidding game, and (iii) weak payment incentives, because we started calling overdue buyers only after the payment period had ended. As part of the encashment procedure, we eventually asked village authorities to enforce payments. It can be expected that local authorities followed our request with varying degrees of rigor and, indeed, default rates are highly clustered by community (Figure 1C.1 in Appendix 1C)³⁰, suggesting that weak incentives were a main reason for defaulting. At the same time, this does not create an upward bias in the bid, since these weak incentives became noticeable only *after* the game. We cannot fully exclude (ii) tricking, though, but our field team presented an official letter by the governmental energy utility, and buyers were informed prior to their bids that a contract will be signed. In the Rwandan context, people are not inclined to dodge responsibility towards the government, so this approach yielded a high commitment. Nevertheless, in the following sections we probe deeper into declining and defaulting and provide adjusted estimates for the WTP.

1.6.1 Incidence

As can be seen in Table 1.6, out of 182 households who won the bidding game, 28 households (15 percent) did not buy a kit. Some of these households (n=6) were not present at the price draw meeting and were thus unaware of their wins, but most attended the meeting (n=22) and declined after they had won the kit. We conservatively treat all 28 households as decliners in the following. Declining is highest among winners of Kit 3 (33 percent). We probe into the correlates of declining in a multivariate regression in Appendix 1B and find some indication that households who did not win their favorite kit or had shorter payment periods have a higher

³⁰ Similar encashment heterogeneities were also observed in Tarozi et al. (2014).

probability to decline (see Table 1B.5 in Appendix 1B for more details). This confirms that declining may disclose an upward bias in the bids.

Table 1.6: Incidence of declining and default

Time		All kits	Kit 1	Kit 2	Kit 3
<i>Declining</i>					
	% of winners declining	15	20	9	33
	N Winners	182	74	93	15
<i>Default</i>					
Deadline period	% of buyers paying full price	18	27	13	10
	% of price paid by all buyers	39	41	37	40
Monitoring period	% of buyers paying full price	66	85	59	20
	% of price paid by all buyers	77	89	72	46
	N Buyers	154	59	85	10

Note: 'Deadline' refers to the randomly allocated one week/six weeks/five months payment periods; 'monitoring' refers to the period until we stopped monitoring payments (at most 11 months after the experiment).

Table 1.6 also summarizes defaulting, showing that only 18 percent of buyers completed their payment before the deadline of their respective payment period. On average, buyers paid between 37 and 41 percent of the full price for the three kits.

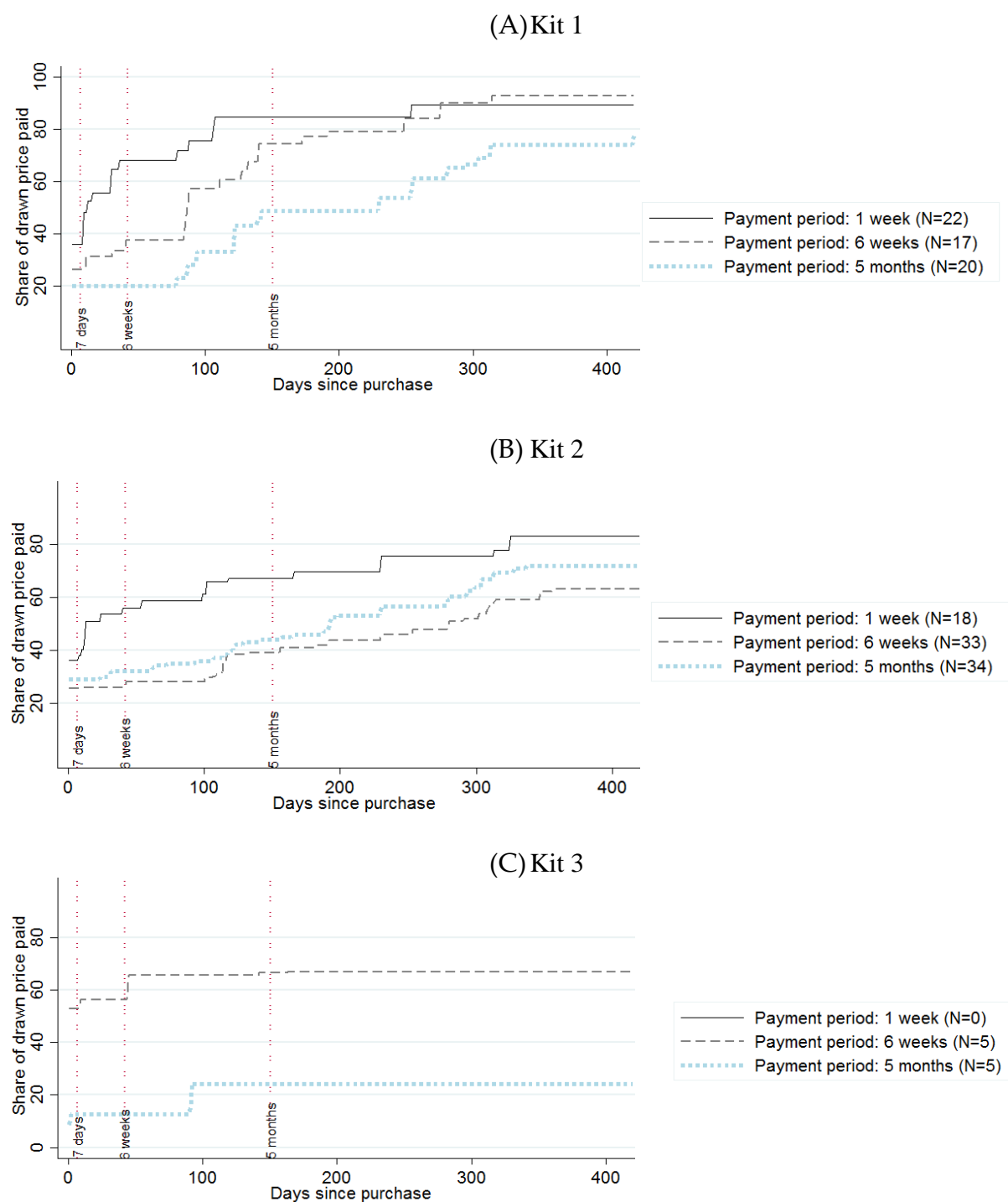
Appendix 1C gives more details on defaulting shares and analyses associated household level variables. After the payment deadlines had expired, we started encashment activities via phone and community authorities during a monitoring period of at most 11 months.^{31,32} This increased the rate of fully paid kits considerably from 18 to 66 percent and the average share of the price paid from 39 to 77 percent.³³ Payment over time is graphically presented in Figure 1.4.

³¹ After these 11 months, our field team eventually asked community authorities to revisit defaulting participants and announce that the kit would have to be returned in case of a further payment delay.

³² The most frequent response to reminder calls was a payment promise (over 50 percent), followed by referring to financial bottlenecks, sickness, and dissatisfaction with mobile money (about 10 percent each).

³³ This payment share is relatively high compared to similar exercises (see, for example, Luoto and Levine 2014 and Tarozzi et al. 2014).

Figure 1.4: Payment over time by payment scheme and kit

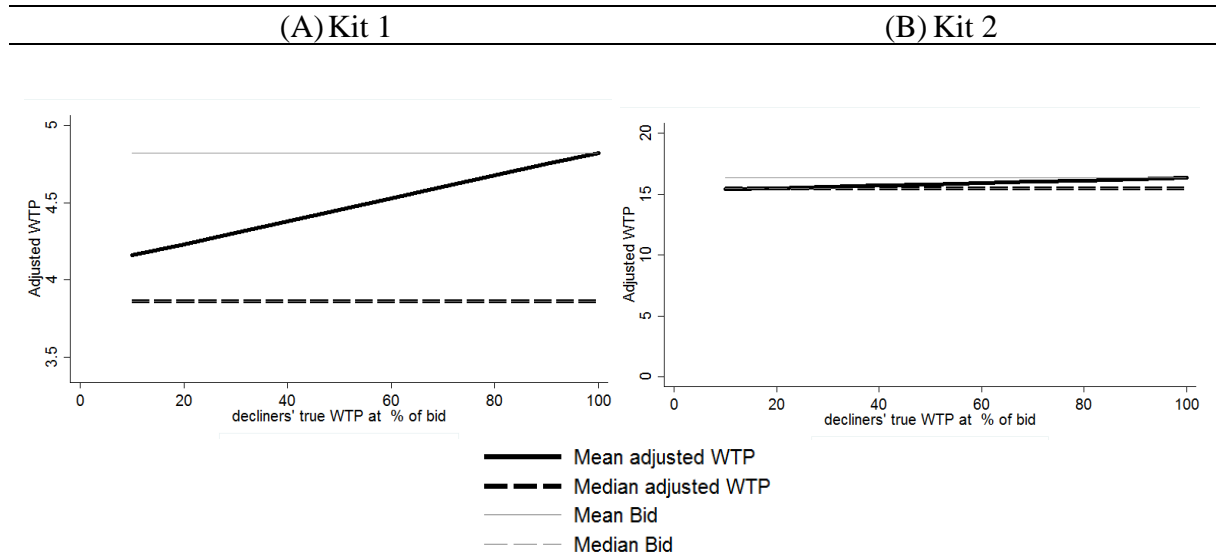


1.6.2 Adjusted willingness to pay estimate

Since we cannot completely rule out biases, we now propose an adjusted WTP that accounts for declining and defaulting. The main challenge hereby is how to handle non-winning households, since we neither observe whether they had declined in case of winning nor their effective payment in case of buying. Below, we provide quantitative solutions to these

challenges for Kit 1 and Kit 2. For Kit 3, we cannot use the same adjustment method because only 15 households won the kit. Instead, we explore potential biases tentatively.

Figure 1.5: Sensitivity of WTP to different decliner bias scenarios (in USD)



Note: We adjust WTP values for declining by setting decliners' WTP to different shares of their bids (10%-100%). The main reason for the flat median curve is that a substantial share of participants (about 30 percent for Kit 1, and 10 percent for Kit 2) made just this median bid (see Figure 1.3, also note that for Kit 1 the median is the lower bound of our price range). This part of the distribution is shifted from the second to the third quartile when we adjust downwards the bid of decliners, but always includes the median. Values for Kit 3 cannot be predicted due to sample size limitations.

We first scrutinize the sensitivity for declining by setting the adjusted WTP of decliners to different shares of their bid (10 percent – 100 percent), thereby assuming different scenarios for how much households might have inflated their bids. To address the aforementioned challenge of handling non-winning households, we predict their propensity to decline³⁴ based on the declining decision in the subsample of winners. Mean values decrease at maximum by 12 percent for Kit 1 and six percent for Kit 2. It is in line with expectation that WTP for Kit 1 is more affected because of the higher share of decliners (see Table 6).

To adjust the WTP of defaulters, we use the payments winners effectively made³⁵. The first challenge hereby is that we cannot observe whether winning households would have paid more in case they had received a higher price draw. In response to this, we take the share of the drawn price that winners effectively paid and multiply it with their bid. We thereby assume that winners would have paid the same share of a higher price. The second challenge is again that we do not observe hypothetical defaulting of non-winning households. To adjust the WTP of

³⁴ As covariates, we use the stated favorite kit, the bid, the price drawn at the village level, the payment scheme, and our full set of control variables. We define the 15 percent of non-winners with the highest propensity to decline as 'hypothetical decliners'.

³⁵ We use payments made in the monitoring period.

the non-winners, we use the winner sample and regress the share of the drawn price that was effectively paid on a set of covariates³⁶ and use the coefficients from this regression to predict the hypothetical shares for the non-winners. We then multiply the hypothetical shares with the non-winners' bids.

As displayed in Table 1.7, adjustments for defaulting reduce the mean WTP by 9 percent for Kit 1 and 28 percent for Kit 2. The median WTP for Kit 1 does not change, while it decreases by 25 percent for Kit 2. The higher defaulting rates for Kit 2 (see Table 1.6) explain the higher sensitivity of the results.

Table 1.7: Adjusted WTP vs. bid (in USD)

	Kit 1 (Full sample)		Kit 2 (Full sample)	
	mean	median	mean	median
Bid	4.8	3.9	16.3	15.5
WTP adjusted for defaulters	4.4	3.9	11.7	11.5
WTP adjusted for defaulters and decliners ¹	4.1	3.9	11.3	10.5
Bid as share of monthly expenditures	20.6	11.6	65.8	37.5
Adjusted WTP (defaulters and decliners) as share of monthly expenditures	18.0	9.7	48.6	22.0
N	323	323	323	323

Note: Due to sample size limitations we cannot calculate the adjusted WTP for Kit 3. We assume decliners' true WTP to be at 50% of their bid. Alternative assumptions do not alter the average WTP substantially (see Figure 1.5 for a sensitivity analysis).

Next, we combine the adjustment for declining and defaulting. We assume that decliners' true WTP is at 50 percent of their bids, and when a non-winning household is predicted both as defaulter and decliner, we conservatively categorize it as a decliner. The mean WTP is further reduced by in total 16 percent for Kit 1 and 31 percent for Kit 2 (for medians see Table 1.7). Our measure of (high) valuation, namely the WTP in relation to households' monthly expenditures, on average, decreases from 21 to 18 percent for Kit 1 and from 66 to 49 percent for Kit 2 (for medians see Table 1.7).

For Kit 3, the problem of declining and defaulting is most salient, where 33 percent (n=5) of winners decline, and buyers pay on average only 46 percent of the full price (see Table 1.6). We therefore adjust the WTP, but without predicting hypothetical defaulting and declining

³⁶ As covariates, we again use the information on the favorite kit, the bid, the price drawn at the village level, the payment scheme, and our full set of control variables.

behavior among non-winners. Rather, we only look at the effectively made payments of buyers and, similar as for Kits 1 and 2, multiply the paid share of the drawn price with their bid.³⁷

As Table 1.8 shows, buyers' adjusted WTP is on average 60 USD, which is about 40 percent of their bid. This gives us an order of magnitude by how much the bids for Kit 3 in our experiment need to be deflated. This also has implications for the relative valuation: Buyers thereby invest 91 percent of their monthly expenditures as compared to the 231 percent that represent their bids.

Table 1.8: Adjusted WTP vs. bid for buyers of Kit 3 (in USD)

	Kit 3 (Only buyers)	
	mean	median
Bid	145.2 (77.4)	148.1 (64.4)
WTP adjusted for defaulters	59.9	39.7
Bid as share of monthly expenditures	230.5 (330.8)	177.8 (177.4)
Adjusted WTP (defaulter) as share of monthly expenditures	91.1	60.0
N	10 (323)	10 (323)

Note: For comparison we display the values of the full sample (from Table 1.3) in parentheses.

1.6.3 Robustness of the effect of relaxing liquidity constraints

To verify whether declining and defaulting compromise the – hitherto insignificant – effects of relaxed liquidity constraints, we re-run our analysis from Table 1.4, i.e., regress the households' bids on the payment schemes. We now control for declining with a dummy and for defaults with the share of the original bid that the household effectively paid.³⁸ Results in Table 1.9 show that the coefficients either remain insignificant (for the six-week payment period) or the magnitude hardly changes (from 0.12 to 0.14 for the five-month extension), suggesting that the effect of relaxing liquidity constraints is robust to a potential bias in the bids induced by defaulters and decliners.

Because the payment periods are important covariates of declining and defaulting, they are included as predictors for hypothetical declining and defaulting. This obviously entails multicollinearity and prevents a straightforward interpretation of the coefficients. Yet, the robustness of our findings does not hinge upon their inclusion in the regression. In the Appendix

³⁷ Adjusting the WTP of the full sample would lead to a lower adjusted WTP because the 10 effectively buying households are likely to be better-off than the non-winning households.

³⁸ Recall from Section 1.6.2: For non-winners, we predict the hypothetical propensity to decline, and treat households above the 85th percentile of the distribution as hypothetical decliners. We furthermore predict the share paid by hypothetical defaulters.

Table 1D.1, we conduct further robustness checks in which we a) do not use the payment schemes as predictors and b) assume that non-winners would not have declined or defaulted. All three approaches have shortcomings, but consistently show that accounting for decliners and defaulters does not alter our results.

Table 1.9: Payment periods and willingness to pay (controlling for defaulting and declining)

	Kit 1		Kit 2	
	Bid	Adjusted Bid	Bid	Adjusted Bid
Six weeks	0.014 (0.808)	0.020 (0.713)	-0.009 (0.898)	-0.027 (0.687)
Five months	0.120 (0.037)**	0.140 (0.014)**	0.070 (0.298)	0.055 (0.403)
HH defaulted (share paid)		-0.002 (0.186)		0.007 (0.000)***
HH declined =1		0.334 (0.000)***		0.130 (0.342)
N	323	323	323	323
<i>Control variables</i>				
Community and date	YES	YES	YES	YES
Socio-economic characteristics	YES	YES	YES	YES
Baseline lighting consumption	YES	YES	YES	YES

Note: We display coefficients from an IR estimation with robust standard errors. The dependent variable is the log of WTP. The base category is a one-week payment period. See Table 1D.1 in Appendix 1D for full regression results including the coefficients of control variables.

1.6.4 Implications for our key findings

We now discuss the implications of a potential, but modest bias in bids – as revealed by adjusted WTP estimates – for the main findings of this chapter:

- (i) the affordability barrier (“WTP is not high enough to reach cost-covering prices”),
- (ii) the relative valuation (“WTP is high relative to total expenditures and expresses households’ high valuation of off-grid solar”)
- (iii) the financing finding (“longer payment periods do not increase WTP”), and
- (iv) the subsidization interpretation (“subsidizing off-grid solar for mass electrification is more socially desirable than subsidizing the grid”).

First, the *affordability* finding holds. Since the adjusted WTP is even lower than the bid, our interpretation that a market-based distribution of off-grid solar excludes large parts of the population is corroborated.

Second, our *relative valuation result* is based on the observation that WTP is high compared to total expenditures, which we interpret as high valuation of solar energy. This is clearly affected

by an upward bias in our WTP estimate. Yet even the average adjusted WTP amounts to shares in expenditures that are substantial (18 percent for Kit 1, and 49 percent for Kit 2). The effective WTP for Kit 3 also still reveals a high valuation, at least for the selective sample of buyers who invest 86 percent of their total monthly expenditures.

Third, our *financing result* has two components. The first component is that the randomly assigned payment schemes do not increase the WTP when accounting for interest rates. This interpretation should be read with care, because default rates raise concerns that the payment periods were not taken sufficiently seriously. The second is that the affordability challenge cannot be overcome by simply relaxing credit constraints. This finding is even strengthened because not taking payment periods seriously is more likely to induce an upward bias for shorter payment periods. It is this second interpretation that is central to the key messages of the chapter (related to the *SEforALL perspective*).

Fourth, the subsidy interpretation changes to the degree that the median *internal return on investment gap* increases from 9, 21, and 115 USD to 9, 26, and 144 USD for Kits 1, 2, and 3, respectively (using median values from Table 1.5, Table 1.7, and Table 1.8). The increase is most substantial for Kit 3, especially considering the self-selected sample. For Kits 1 and 2, the increase is less noticeable or even absent. The qualitative conclusion based on our review of the literature in Section 1.5.2 should therefore hold.

1.6.5 Transaction costs

Declining and especially defaulting constitute an interesting observation beyond their implications for our findings. Encashment challenges are typical for many rural African markets, especially as they reach out to poorer population strata to achieve universal access goals. These challenges thereby raise substantial real-world transaction costs in disseminating market-based off-grid solar power to the rural poor.³⁹ The PAYG model we use resembles that of many providers, in that participants agree to pay small instalments over time via mobile money. The high transaction costs induced by PAYG related encashment is also emphasized in Lighting Global (2018, p. 96) for off-grid solar companies operating in Africa and Asia. Defaulting is especially problematic when companies enter new and probably poorer segments of the population (p. 10). Yet, novel PAYG features, for example those that turn off the kit remotely in case of non-payment, are likely to improve payment behavior. At the same time,

³⁹ See Levine et al. (2018) and Bensch and Peters (2019) for a discussion of transaction costs for the case of cookstoves and Tarozzi et al. (2014) for malaria bed nets.

risks and transaction costs of the current PAYG schemes will remain high nevertheless (Collings and Munyehirwe 2016, Muchunku et al. 2018).

1.7 Conclusion

This chapter has examined the revealed WTP for three different solar lighting technologies of poor off-grid households in rural Rwanda. We find that households reveal a substantial valuation as compared to their low expenditure levels, but that the WTP is nevertheless clearly below the market prices of the three kits. Longer payment periods do not considerably alter the WTP. These findings are robust to accounting for purchase decliners and payment defaults of some participants in our experiment, which are both frequently encountered issues in real-purchase offer experiments in the field.

Interpreted from the *SEforALL perspective*, our results question whether the international community can achieve universal access to electricity with its current purely market-based approach, even when combined with smarter payment schemes. Highly-praised off-grid solar companies like *M-Kopa*, *BBOX* and *d.light* have been remarkably successful in a few countries, but most likely sell to better off strata and (peri-) urban areas. That said, some external validity caveats apply (see Peters, Langbein and Roberts 2018). For example, as off-grid solar is disseminated into rural communities at scale, social learning might increase the WTP over time. Moreover, we acknowledge the limits of an experiment in one country, especially considering the huge Rwandan electricity grid extension programme, EARP. This programme might affect expectations regarding future access to grid electricity, and hence reduce the WTP for off-grid solutions (see Burgess et al. 2019). Yet, the affordability result is also informed by our previous work on the willingness and ability to pay for electricity in other countries (see Bensch et al. 2018 for a study on Burkina Faso, as well as Grimm and Peters 2016, Peters and Sievert 2016 and Steinbuks and Sievert 2019 for reviews of several countries). This synthesis will be transferable to many other regions, especially to the large number of poor countries in Central and West Africa that are so far only marginally covered by the off-grid solar business.

Turning to the *Social Planner's perspective*, we have argued that external effects of electrification are more likely to close the *internal return on investment gap* of small-scale off-grid solar electrification than the gap for on-grid electrification. The gap refers to the difference between the cost of electricity provision and the benefits internalized by its users. This result is mainly driven by high investment costs of on-grid electrification, and to a lesser extent by households' low internalization of electrification benefits. More precisely, our brief literature review has shown that off-grid solar does not create a massive socio-economic transformation

but does yield positive pro-poor impacts that are noteworthy relative to the low investment cost. Earlier research has also shown that electricity consumption levels even in grid-connected areas in rural Africa are very modest (see Chaplin et al. 2017, Lenz et al. 2017, Peters et al. 2011, and Taneja 2018). Such low consumption levels can well be met by off-grid solar energy. It is furthermore worth mentioning that the WTP values we measure are low in absolute terms but quite considerable in relation to households' budgets, indicating that households prioritize off-grid electricity over many other goods.⁴⁰

Bringing together these two perspectives, our findings suggest that a subsidization policy that decreases end-user prices is necessary and – from a social planner's perspective – justified to reach the short-term SEforALL universal access goal. We thereby complement Lee et al. (2019) who rightly emphasize the high costs of grid extension. Electricity access is nevertheless an important service for hitherto unconnected populations, and its subsidization can be cost-effective if off-grid technologies are used. Any subsidy scheme should encompass sustainable funding, pro-poor targeting, and a clearly communicated phasing-out strategy. Urpelainen (2018) compellingly conceptualizes how energy access subsidies could be practically implemented. Needless to say, off-grid solar does not replace the necessity to build infrastructure. Yet, instead of rolling out the grid to virtually every rural village in Africa, on-grid investments could be concentrated in thriving rural regions with high business potential or in industrial zones to which firms can relocate. This, in turn, requires accurate demand forecasts that identify high potential regions for connection (Taneja 2018). Such an integrated on-grid-off-grid strategy would enable industrial development and at the same time achieve broad and more equally distributed access to electricity (Trotter et al. 2019).

⁴⁰ With a focus on educational outcomes, Stojanovski et al. (2018), for example, compare the effects of solar lanterns to other small-scale household investments like school backpacks and alarm clocks.

References Chapter 1

Abdul-Salam, Yakubu, and Euan Phimister. 2019. Modelling the impact of market imperfections on farm household investment in stand-alone solar PV systems. *World Development* 116: 66-76.

Aevarsdottir, Anna M., Nicholas Barton, and Tessa Bold. 2017. The impacts of rural electrification on labor supply, income and health: experimental evidence with solar lamps in Tanzania. International Growth Centre. Working Paper.

AFR, AMIR, and MicroFinanza Rating. 2015. Assessment of the Rwandan microfinance sector performance, <http://www.afr.rw/wp-content/uploads/2016/03/Rwanda-MF-Sector-Assessment-October-2015.pdf>.

Ahuja, Amrita, Sarah Baird, Joan Hamory Hicks, Michael Kremer, Edward Miguel, and Shawn Powers. 2015. When should governments subsidize health? The case of mass deworming. *The World Bank Economic Review* 29: S9-S24.

Bates, Mary A., Rachel Glennerster, Kamilla Gumedde, and Esther Duflo. 2012. The price is wrong. *Fields Actions Science Reports (FACTS)*, Special Issue 4.

Bauchet, Jonathan, and Jonathan Morduch. 2019. Paying in pieces: A natural experiment on demand for life insurance under different payment schemes. *Journal of Development Economics* 139: 69-77.

Baurzhan, Saule, and Glenn P. Jenkins. 2016. Off-grid solar PV: Is it an affordable or appropriate solution for rural electrification in Sub-Saharan African countries? *Renewable and Sustainable Energy Reviews* 60: 1405-1418.

Beaman, Lori, Ariel Ben Yishay, Jeremy Magruder, and A. Mushfiq Mobarak. 2018. Can network theory-based targeting increase technology adoption? (No. w24912). National Bureau of Economic Research.

Beltramo, Theresa, Garrick Blalock, David I. Levine, and Andrew M. Simons. 2015. The effect of marketing messages and payment over time on willingness to pay for fuel-efficient cookstoves, *Journal of Economic Behavior & Organization* 118: 333-345.

Ben Yishay, Ariel, and A. Mushfiq Mobarak. 2019. Social learning and incentives for experimentation and communication. *The Review of Economic Studies* 86(3): 976-1009.

Ben Yishay, Ariel, Andrew Fraker, Raymond Guiteras, Giordano Palloni, Neil B. Shah, Stuart Shirrell, and Paul Wang. 2017. Microcredit and willingness to pay for environmental quality: Evidence from a randomized-controlled trial of finance for sanitation in rural Cambodia. *Journal of Environmental Economics and Management* 86: 121-140.

Bensch, Gunther, and Jörg Peters. 2019. One-off subsidies and long-run adoption—Experimental evidence on improved cooking stoves in Senegal. *American Journal of Agricultural Economics* 102(1): 72-90.

Bensch, Gunther, Michael Grimm, and Jörg Peters. 2015. Why do households forego high returns from technology adoption? Evidence from improved cooking stoves in Burkina Faso. *Journal of Economic Behavior & Organization* 116: 187-205.

Bensch, Gunther, Jörg Peters, and Maximiliane Sievert. 2017. The lighting transition in rural Africa — From kerosene to battery-powered LED and the emerging disposal problem. *Energy for Sustainable Development* 39: 13-20.

Bensch, Gunther, Michael Grimm, Maximilian Huppertz, Jörg Langbein, and Jörg Peters. 2018. Are promotion programs needed to establish off-grid solar energy markets? Evidence from rural Burkina Faso. *Renewable and Sustainable Energy Reviews* 90: 1060-1068.

Bernard, Tanguy. 2012. Impact Analysis of Rural Electrification Projects in Sub-Saharan Africa. *World Bank Research Observer* 27(1): 33–51.

Berry, James, Greg Fischer, and Raymond P. Guiteras. 2020. Eliciting and utilizing willingness to pay: evidence from field trials in Northern Ghana. *Journal of Political Economy* 128(4): 1436-1473.

Bos, Kristine, Chaplin, Duncan, and Arif Mamun. 2018. Benefits and challenges of expanding grid electricity in Africa: A review of rigorous evidence on household impacts in developing countries. *Energy for Sustainable Development* 44: 64-77.

Burgess, Robin, Michael Greenstone, Nicholas Ryan, and Anant Sudarshan. 2019. Demand for electricity in a poor economy. Mimeo.

Cameron, Trudy A., and Daniel D. Huppert. 1989. OLS versus ML estimation of non-market resource values with payment card interval data. *Journal of Environmental Economics and Management* 17(3): 230-246.

Chaplin, Duncan, Arif Mamun, Ali Protik, John Schurrer, Divya Vohra, Kristine Bos, Hannah Burak, Laura Meyer, Anca Dumitrescu, Christopher Ksoll, and Thomas Cook. 2017. Grid Electricity Expansion in Tanzania by MCC: Findings from a Rigorous Impact Evaluation. Report submitted to the Millennium Challenge Corporation, Washington, DC: Mathematica Policy Research, <https://www.mathematica.org/our-publications-and-findings/publications/grid-electricity-expansion-in-tanzania-by-mcc-findings-from-a-rigorous-impact-evaluation>.

Cohen, Jessica, and Pascaline Dupas. 2010. Free distribution or cost-sharing? Evidence from a malaria prevention experiment. *Quarterly Journal of Economics* 125(1): 1-45.

Collings, Simon, and Anicet Munyehirwe. 2016. Pay-as-you-go solar PV in Rwanda: evidence of benefits to users and issues of affordability, *Fields Actions Science Reports (FACTS)* 15: 94-103.

Devoto, Florencia, Esther Duflo, Pascaline Dupas, William Parienté, and Vincent Pons. 2012. Happiness on tap: Piped water adoption in urban Morocco. *American Economic Journal: Economic Policy*, 4(4): 68-99.

Dinkelman, Taryn. 2011. The effects of rural electrification on employment: New evidence from South Africa. *The American Economic Review* 101(7): 3078-3108.

Dupas, Pascaline. 2014. Short-run subsidies and long-run adoption of new health products: Evidence from a field experiment. *Econometrica* 82(1): 197–228.

Foster, Andrew D., and Mark R. Rosenzweig. 2010. Microeconomics of technology adoption. *Annual Review of Economics* 2(1): 395-424.

Fowlie, Meredith, Yashraj Khaitan, Catherine Wolfram, and Derek Wolfson. 2018. Solar microgrids and remote energy access – How weak incentives can undermine smart technology. International Growth Center, Final Report. E-89226-INC-1, <https://www.theigc.org/wp-content/uploads/2018/06/Fowlie-et-al-2018-Final-report.pdf>.

Furukawa, Chishio. 2014. Do solar lamps help children study? Contrary evidence from a pilot study in Uganda. *Journal of Development Studies* 50(2): 319-341.

Grimm, Michael, and Jörg Peters. 2016. Solar off-grid markets in Africa - Recent dynamics and the role of branded products. *Fields Actions Science Reports (FACTS)* 15: 160-163.

Grimm, Michael, Anicet Munyehirwe, Jörg Peters, and Maximiliane Sievert. 2017. A first step up the energy ladder? Low cost solar kits and household's welfare in rural Rwanda. *World Bank Economic Review* 31(3): 631-649.

Guiteras, Raymond, David I. Levine, Thomas Polley, and Brian Quistorff. 2016. Credit constraints, discounting and investment in health: Evidence from micropayments for clean water in Dhaka. Unpublished manuscript.

IEA. 2017. Energy Access Outlook 2017. The International Energy Agency (IEA), Paris.

Kaas, Klaus Peter, and Heidrun Ruprecht. 2006. Are the Vickrey Auction and the BDM-Mechanism Really Incentive Compatible? *Schmalenbach Business Review* 58: 37-55.

Kassem, Dana. (2018). Does electrification cause industrial development? Grid expansion and firm turnover in Indonesia. Unpublished manuscript.

Khandker, Shahidur R., Douglas F. Barnes, and Hussain A. Samad. 2013. Welfare impacts of rural electrification: A panel data analysis from Vietnam. *Economic Development and Cultural Change* 61(3): 659–692.

Kremer, Michael, and Edward Miguel. 2007. The illusion of sustainability. *Quarterly Journal of Economics* 122(3): 1007–1065.

Kudo, Yuya, Abu S. Shonchoy, and Kazushi Takahashi. 2017. Can solar lanterns improve youth academic performance? experimental evidence from Bangladesh. *The World Bank Economic Review*, lhw073.

Kudo, Yuya, Abu S. Shonchoy, and Kazushi Takahashi. 2018. Short-term impacts of solar lanterns on child health: experimental evidence from Bangladesh. *The Journal of Development Studies* 1-18.

Lam, N. L., G. Muhwezi, F. Isabirye, K. Harrison, I. Ruiz-Mercado, E. Amukoye, ... and M. N. Bates. 2018. Exposure reductions associated with introduction of solar lamps to kerosene lamp-using households in Busia County, Kenya. *Indoor Air* 28(2): 218-227.

Lee, Kenneth, Edward Miguel, and Catherine Wolfram. 2020. Experimental evidence on the economics of rural electrification. *Journal of Political Economy* 128(4): 1523-1656.

Lemaire, Xavier. 2018. Solar home systems and solar lanterns in rural areas of the Global South: What impact? *Wiley Interdisciplinary Reviews: Energy and Environment*, 7(5), e301.

Lenz, Luciane, Anicet Munyehirwe, Jörg Peters, and Maximiliane Sievert. 2017. Does large scale infrastructure investment alleviate poverty? Impacts of Rwanda's electricity access roll-out program, *World Development* 89: 88-110.

Levine, David I., Theresa Beltramo, Garrick Blalock, Carolyn Cotterman, and Andrew M. Simons. 2018. What impedes efficient adoption of products? Evidence from randomized sales offers for fuel-efficient cookstoves in Uganda. *Journal of the European Economic Association* (forthcoming).

Lighting Global. 2016. *Off-grid solar market trends report 2016*.
https://www.lightingglobal.org/wp-content/uploads/2016/03/20160301_OffGridSolarTrendsReport.pdf .

Lighting Global. 2018. *Off-Grid Solar Market Trends Report 2018*.
https://www.lightingglobal.org/wp-content/uploads/2018/03/2018_Off_Grid_Solar_Market_Trends_Report_Full.pdf .

- Lipscomb, Molly, A. Mushfiq Mobarak, and Tania Barham.** 2013. Development effects of electrification: Evidence from topographic placement of hydropower plants in Brazil. *American Economic Journal: Applied Economics* 5(2): 200-231.
- Litzow, Erin L., Subhrendu K. Pattanayak, and Tshering Thinley.** 2013. Returns to rural electrification: Evidence from Bhutan. *World Development* 121: 75-96.
- Luoto, Jill, and David I. Levine.** 2014. Mobile phones, rent-to-own payments & water filters: Evidence from Kenya. Rand Working Paper WR-1039.
- MININFRA** (Ministry of Infrastructure). 2016. Rural Electrification Strategy, http://www.mininfra.gov.rw/fileadmin/user_upload/aircraft/Rural_Electrification_Strategy.pdf.
- MININFRA** (Ministry of Infrastructure). 2018. Energy Sector Strategic Plan 2018/2019 - 2023/24. http://www.mininfra.gov.rw/fileadmin/user_upload/infos/Final_ESSP.pdf.
- Mobarak, A. Mushfiq, Puneet Dwivedi, Robert Bailis, Lynn Hildemann, and Grant Miller.** 2012. Low demand for nontraditional cookstove technologies. *Proceedings of the National Academy of Sciences of the United States of America* 109(27): 10815-10820.
- Muchunku, Charles, Kirsten Ulsrud, Debajit Palit, and Wim Jonker-Klunne.** 2018. Diffusion of solar PV in East Africa: What can be learned from private sector delivery models?. *Wiley Interdisciplinary Reviews: Energy and Environment*, 7(3): e282.
- Neelsen, Sven, and Jörg Peters.** 2011. Electricity usage in micro-enterprises—Evidence from Lake Victoria, Uganda. *Energy for Sustainable Development* 15(1): 21-31.
- Pattanayak, Subhrendu K., Marc A. Jeuland, Jessica J. Lewis, Faraz Usmani, Nina Brooks, Vasundhara Bhojvaid, ..., and Veerabhadran Ramanathan.** 2019. Experimental evidence on promotion of electric and improved biomass cookstoves. *Proceedings of the national Academy of Sciences*, 116(27): 13282-13287.
- Peters, Jörg, and Maximiliane Sievert.** 2016. Impacts of rural electrification revisited – The African context. *Journal of Development Effectiveness* 8(3): 327–345.
- Peters, Jörg, Jörg Langbein, and Gareth Roberts.** 2018. Generalization in the tropics—development policy, randomized controlled trials, and external validity. *The World Bank Research Observer*, 33(1), 34-64.
- Peters, Jörg, Maximiliane Sievert, and Michael A. Toman.** 2019. Rural Electrification through Mini-Grids: Challenges Ahead. *Energy Policy* 132: 27-31.
- Peters, Jörg, Collin Vance, and Marek Harsdorff.** 2011. Grid extension in rural Benin: Micro-manufacturers and the electrification trap. *World Development*, 39(5): 773–783.
- Rom, Adina, Isabel Günther, and Kat Harrison.** 2016. Economic Impact of Solar Lighting – A Randomized Field Experiment in Kenya. Version v1, December 2016.
- Rud, Juan Pablo.** 2012. Electricity provision and industrial development: Evidence from India. *Journal of Development Economics* 97(2): 352–367.
- Samad, Hussain A., Shahidur R. Khandker, M. Asaduzzaman, and Mohammed Yunus.** 2013. The benefits of solar home systems: An analysis from Bangladesh. World Bank Policy Research Working Paper 6724, World Bank, Washington D.C.
- Sievert, Maximiliane, and Jevgenijs Steinbuks.** 2019. Willingness to Pay for Electricity Access in Extreme Poverty. World Bank Policy Research Working Paper 8906.

Stojanovski, Ognen., Mark Thurber, and Frank Wolak. 2017. Rural energy access through solar home systems: Use patterns and opportunities for improvement. *Energy for Sustainable Development* 37, 33-50.

Stojanovski, Ognen, Mark Thurber, Frank Wolak, George Muwowo, and Kat Harrison. 2018. Assessing Opportunities for Solar Lanterns to Improve Educational Outcomes in Rural Off-Grid Regions: Challenges and Lessons from a Randomized Controlled Trial. <https://ssrn.com/abstract=3289855>.

Sustainable Energy for All (SEforALL). 2013. Sustainable Energy for All global tracking framework consultation document. <http://www.seforall.org/tracking-progress/>.

Sustainable Energy for All. 2014. Rapid Assessment Gap Analysis Rwanda. https://www.seforall.org/sites/default/files/Rwanda_RAGA_EN_Released.pdf.

Taneja, Jay. 2018. If You Build It, Will They Consume? Key Challenges for Universal, Reliable, and Low-Cost Electricity Delivery in Kenya. Center for Global Development Working Paper 491, Washington, DC.

Tarozzi, Alessandro, Aprajit Mahajan, Brian Blackburn, Dan Kopf, Lakshmi Krishnan, and Joanne Yoong. 2014. Micro-loans, insecticide-treated bednets, and malaria: evidence from a randomized controlled trial in Orissa, India. *American Economic Review* 104(7): 1909-1941.

Trotter, Philipp. A., Nathaniel J. Cooper, and Peter R. Wilson. 2019. A multi-criteria, long-term energy planning optimisation model with integrated on-grid and off-grid electrification—The case of Uganda. *Applied Energy*, 243, 288-312.

Urpelainen, Johannes. 2018. Vouchers can create a thriving market for distributed power generation in developing countries. *Energy Research & Social Science* 46: 64-67.

Urpelainen, Johannes, and Semee Yoon. 2017. Can product demonstrations create markets for sustainable energy technology? A randomized controlled trial in rural India. *Energy Policy* 109: 666-675.

van de Walle, Dominique, Martin Ravallion, Vibhuti Mendiratta, and Gayatri Koolwal. 2017. Long-term gains from electrification in rural India. *World Bank Economic Review* 31(2): 385-411.

World Bank. 2009. Unit costs of infrastructure projects in Sub-Saharan Africa. Africa infrastructure country diagnostic. Background Paper (11).

World Development Indicators. 2018. <https://data.worldbank.org/indicator/DT.ODA.ALLD.CD?end=2016&locations=ZG&start=2002>.

Yadav, Prabhakar, Anthony P. Heynen, and Debajit Palit. 2019. Pay-As-You-Go financing: A model for viable and widespread deployment of solar home systems in rural India. *Energy for Sustainable Development*, 48, 139-153.

Yoon, Semee, Johannes Urpelainen, and Milind Kandlikar. 2016. Willingness to Pay for Solar Lanterns: Does the Trial Period Play a Role? *Review of Policy Research* 33 (3): 291-315.

Appendix Chapter 1

This appendix is published as an electronic appendix to complement the published paper.

Appendix 1A: Experiment Instructions

I now invite you to buy the kit which I just presented to you. The sale is different from usual sales, as the price is not yet fixed. The sale works as follows. You will make a bid for the kit, which means you will tell me the exact price you are willing to pay for it. It is ideal to indicate the maximum price you are willing to pay. When you make your bid, remember that you spend a certain amount of money every month on energy to light your house, for example on batteries, candles or kerosene. For all these energy sources, people in rural Rwanda spent on average 2,600 RWF per month. You could therefore save this amount if you buy the kit. After you make your bid, I will draw a price from this envelope during a village meeting this afternoon *[show envelope]*. There are different prices written on pieces of paper in this envelope. The smallest price is 3,000 RWF (10,000 RWF, 90,000 RWF) and the highest is 10,000 RWF (30,000 RWF, 140,000).

If the price you offer now is lower than the price I draw, you cannot buy the kit. If the price you offer now is higher than the price I draw, you can buy the kit for the price I draw. You only have the option to bid once, and you cannot change your bid afterwards. Hence, if your bid is lower than the price I draw, you cannot buy the kit.

After the price drawing in the village meeting, you will have to sign a purchase contract if you won the price drawing. If you cannot pay immediately, you have 7 days (6 weeks, 5 months) to pay for the kit in installments via mobile money. If you want to, you can make an advance payment today. Hence, please make a bid, which you are able to pay within 7 days (6 weeks, 5 months).

We will not inform the others about the price you offer to pay and your result of the game will stay confidential.

I will now give you an example, such that you can better understand the sale process. Imagine I offered you a mobile phone with the same rules. You could for example say that you are ready to pay 3,000 RWF for this phone. Then we draw a price from an envelope.

- The price we draw from the envelope could for example be 2,000 RWF. What would happen in this case?
[Wait for the answer. The correct answer is: I would buy the phone for 2,000 RWF]
- What would happen if you offer 3,000 RWF and the price we draw from the envelope is 3,500 RWF?
[Wait for the answer. The correct answer is: I cannot buy the phone. Explain again in your own words, if necessary, ask for questions, and give another hypothetical example with an imaginary product (not a solar kit) if necessary.]

Remember that you cannot change the price you offer after the price drawing from the envelope. This means, you can only make one bid. Also, remember that you have to pay the price in 7 days (6 weeks, 5 months). In addition, be aware that you cannot buy the kit, even if your offer is only slightly less than the price I draw. *[Verify that there are no other questions. Ask for the bid and assure yourself that the participant is convinced of it].*

Appendix 1B: Declined purchase – Incidence and drivers

After the bidding game, 28 out of 182 winning households declined to buy the kit. This appendix describes incidence and drivers of declination in more detail. It shows that declining occurs for all kits and payment periods but is particularly frequent among households that made relatively high bids for Kit 1 and, in general, among households that did not win their favorite kit.

Table 1B.1 shows by kit the number of households winning a bidding game, those being absent at the price draw and sales meeting, those declining to purchase after the meeting, and those effectively buying a kit. In the following, we refer to all 28 households, i.e., those that declined indirectly by not coming to the meeting and those that declined directly, as decliners.

Table 1B.1: Sales outcomes, by kit

Number of households	Kit 1	Kit 2	Kit 3
win in experiment	74	93	15
absent at meeting	1	2	3
decline to sign contract	14	6	2
effective sales	59	85	10

Declining occurs for all kits and for all randomized payment schemes. For Kit 2, more households with shorter payment periods declined, for Kit 3 we observe the opposite (see Table 1B.2). Furthermore, declining occurs in 13 out of the 16 communities (not shown).

Table 1B.2: Purchase decline, by kit and payment scheme

Number of households	Kit 1	Kit 2	Kit 3
Payment scheme: 1 week	5	6	0
Payment scheme: 6 weeks	5	2	2
Payment scheme: 5 months	5	0	3
Total	15	8	5

During the bidding game, we asked households for the kit they would prefer to win. Notably, declining is much higher among households that did not win their favorite kit (71 percent of buyers and only 27 percent of decliners won their favorite kit, see Table 1B.3). This suggests that declining is associated with the disappointment of not winning the favorite kit. In absolute numbers, only six households of the 28 decliners were present at the meeting and won their favorite kit. However, this explanation does not apply to Kit 3, as all decliners present during the meeting won their favorite kit.

Table 1B.3: Winning of favorite kit among buyers and decliners, by kit

	All kits	Kit 1	Kit 2	Kit 3
% winning favorite kit among buyers	0.71	0.39	0.91	1.00
% winning favorite kit among decliners present at meeting	0.27	0.21	0.17	1.00
N winning favorite kit among decliners present at meeting	6	3	1	2

Furthermore, there is no clear pattern when comparing the average bids of decliners and buyers (Table 1B.4). For Kit 1, the decliners' bid is clearly higher than the average bid of winners. This may suggest that Kit 1 decliners overstated their WTP, thereby leading to an upward bias. Yet, for Kit 2 and Kit 3 there are only slight differences in opposite directions.

Table 1B.4: Bid of decliners versus buyers among winners, by kit

	Kit 1	Kit 2	Kit 3
Buyers' bid			
Mean	5.44	21.76	145.16
Median	5.15	19.32	148.12
Decliners' bid			
Mean	7.00	22.86	141.68
Median	6.44	20.61	141.68
Increase in percent (decliners vs. buyers)	29	5	-2
	25	7	-4

We now look at the correlates of declining in a multivariate regression (Table 1B.5), which shows that drivers of declining differ for the three kits. For Kit 2, important drivers of declining are winning the favorite kit, the price drawn, payment schemes, and ownership of a modern electricity source. In contrast, households with a higher bid, higher phone charging expenditures and lower (non-energy) expenditures are more likely to decline Kit 1.

Table 1B.5: Drivers of declining, by kit

	(1) All winning households (Kit 1 – 3)	(2) Only winners Kit 1	(3) Only winners Kit 2
Household won favorite kit	-0.181 (0.063)*	-0.055 (0.773)	-0.260 (0.130)
Bid	0.000 (0.974)	0.039 (0.087)*	-0.006 (0.225)
Price drawn	0.000 (0.973)	0.101 (0.843)	0.133 (0.000)***
Payment period: 6 weeks	-0.058 (0.559)	0.003 (0.986)	-0.139 (0.342)
Payment period: 5 months	-0.125 (0.062)*	-0.113 (0.376)	-0.189 (0.104)
Female respondent	0.049 (0.251)	0.038 (0.724)	0.025 (0.773)
Head of HH years of education	-0.001 (0.967)	-0.018 (0.540)	0.006 (0.523)
HH size	-0.004 (0.854)	0.059 (0.232)	-0.024 (0.435)
Head of HH is a farmer	0.124 (0.059)*	-0.011 (0.871)	0.038 (0.715)
Share of students in HH	-0.001 (0.400)	-0.004 (0.275)	0.002 (0.469)
House with tile roofing	-0.145 (0.123)	-0.568 (0.245)	-0.050 (0.575)
Monthly non-energy expenditures	-0.001 (0.028)**	-0.001 (0.000)***	-0.000 (0.342)
Monthly phone charging expenditures	0.010 (0.661)	0.053 (0.048)**	0.009 (0.803)
Monthly energy expenditures	-0.010 (0.508)	-0.041 (0.574)	-0.000 (0.992)
Owns car battery	0.224 (0.336)	0.504 (0.179)	-0.209 (0.035)**
Owns rechargeable lamp	0.111 (0.125)	0.073 (0.459)	-0.053 (0.283)
Owns solar kit	0.004 (0.948)	0.021 (0.913)	-0.099 (0.569)
Won Kit 2	-0.119 (0.497)	-	-
Won Kit 3	0.088 (0.932)	-	-
Constant	0.404 (0.017)**	0.009 (0.997)	-1.547 (0.000)***
N	182	74	93
R-squared	0.348	0.404	0.538

Note: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$ denote statistical significance. We display results from a Linear Probability Model. P-Values are displayed in parentheses. The sample is restricted to the winners of the three kits. The outcome variable is a binary variable taking the value one for purchase decline. The base category for payment period is one week. The base category for Kit won is Kit 1. We control for community and day count. Standard errors are robust to heteroscedasticity and serial-correlation within communities. Monthly energy expenditures exclude expenditures on wood and rechargeable lamp charging.

Appendix 1C: Payment defaults – Incidence and drivers

After signing the purchase contract, 18 percent of buyers paid the kits' full prices within their payment periods (one week, six weeks, five months) and 66 percent in the monitoring period. This section disentangles default further and discusses potential drivers. Table 1C.1 disaggregates payment performances by kit for deadline and monitoring periods (see Section 1.6.1) among buyers.

Table 1C.1: Propensity to pay (share of price effectively paid), by kit and payment period

Time		Kit 1	Kit 2	Kit 3
Deadline period				
	Paid 0 %	27.1	11.8	10.0
	Paid 1-50 %	42.4	65.9	60.0
	Paid 51-99 %	3.4	9.4	20.0
	Paid 100 %	27.1	11.8	10.0
Monitoring period				
	Paid 0 %	5.1	7.1	10.0
	Paid 1-50 %	6.8	23.5	50.0
	Paid 51-99 %	3.4	10.6	20.0
	Paid 100 %	84.7	58.8	20.0
	N Buyers	59	85	10

Note: 'Deadline' refers to the randomly allocated one week/six weeks/five months payment periods, 'monitoring' refers to the period until we stopped monitoring repayments (at most 11 months after the experiment).

In Table 1C.2 we look at determinants of the share of the final price that has been effectively paid by the sample of buyers, which can also be interpreted as the propensity to pay. The regression is only possible for the buyers of Kit 1 and Kit 2. For sample size reasons we cannot perform a similar analysis for the 10 buyers of Kit 3.

First, we look at a potential correlation between the bid submitted during the purchase offer game and the payment share. There are no clear patterns; the coefficient is insignificant and has a positive sign for Kit 1 and a negative sign for Kit 2. Second, we examine whether the payment share is correlated with the gap between the bid and the randomly allocated price (bid minus price). A large gap can indicate inflated bids by some participants, suggesting participants did not take the deal during the game or the payment duties seriously. The other interpretation is that a large gap indicates luck of the bidder and thus should lead to a higher paid share and a positive sign. For Kit 2 the coefficient is positive, but insignificant, while it is negative and significant for Kit 1. Third, the regression results again indicate that there is no clear effect of the randomized payment periods on the payment share.

Table 1C.2: Correlates of the payment share in monitoring phase, by kit

	Kit 1	Kit 2
Expressed bid in bidding game	4.939 (0.327)	3.161 (0.102)
Gap between bid and price drawn	-7.633 (0.050)**	-2.106 (0.308)
Payment period: 6 weeks	3.021 (0.646)	5.847 (0.434)
Payment period: 5 months	-4.366 (0.499)	3.334 (0.594)
<i>Community and time</i>		
Day count	-0.169 (0.032)**	4.647 (0.066)*
Community Code = 3	-52.200 (0.000)***	37.526 (0.177)
Community Code = 4	-15.545 (0.069)*	2.331 (0.947)
Community Code = 5	-46.433 (0.002)***	-21.100 (0.203)
Community Code = 6	-24.914 (0.096)*	-41.160 (0.070)*
Community Code = 7	-	13.455 (0.432)
Community Code = 8	-	-157.709 (0.049)***
Community Code = 9	-8.574 (0.523)	-
Community Code = 10	-21.529 (0.349)	-425.088 (0.044)
Community Code = 11		27.901 (0.551)
Community Code = 13	-14.891 (0.026)**	34.694 (0.168)
Community Code = 14	-	32.853 (0.105)
<i>Socio-economic characteristics</i>		
Female respondent	-3.119 (0.609)	-3.611 (0.731)
HoH years of education	3.397 (0.257)	0.453 (0.741)
HH size	5.424 (0.166)	4.008 (0.133)
HoH is a farmer	10.452 (0.441)	5.802 (0.534)
Share of students in HH	-0.092 (0.271)	-0.152 (0.532)
House with tile roofing	-	57.195 (0.129)
Monthly non-energy expenditures (USD)	-0.080 (0.228)	-0.130 (0.129)

...

Table 1C.2 continued

	Kit 1	Kit 2
<i>Baseline energy consumption</i>		
Monthly phone charging expenditures	-0.811 (0.861)	-3.498 (0.651)
Monthly energy expenditures	-6.155 (0.318)	2.807 (0.047)**
Owens a car battery	18.184 (0.251)	-12.323 (0.272)
Owens a rechargeable lamp	14.771 (0.253)	18.759 (0.051)*
Owens solar lights	9.618 (0.285)	-21.520 (0.632)
Constant	60.809 (0.056)*	-41.725 (0.409)
N	59	85
R-squared	0.649	0.578

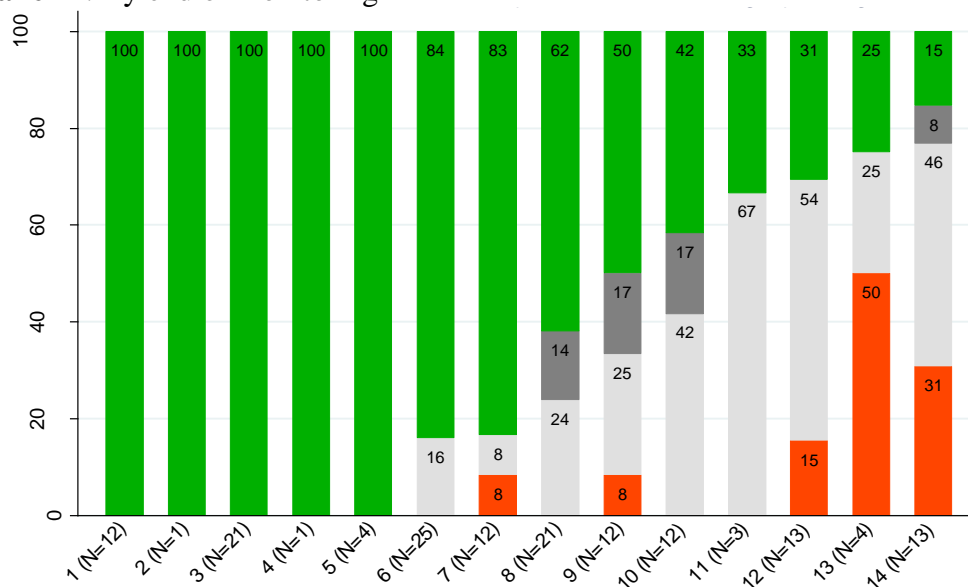
*Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ denote statistical significance. We display results from an OLS estimation. The outcome variable is the share effectively paid within the monitoring phase. Monitoring refers to the extended time frame of reminder calls and inclusion of community authority. The base category for payment period is one week. Robust standard errors are clustered on the community level. Monthly energy expenditures exclude expenditures on wood and rechargeable lamp charging.*

A fourth impression from Table 1C.2 is that communities explain a considerable part of the variation in the payment share. Panel A and Panel B in Figure 1C.1 show, first, a stark increase in payment from the deadline to the end of the monitoring period. Second, especially for the monitoring period, they reveal that both defaulting, and payment compliance are clustered by community, i.e., some communities reveal very high shares of full payment, and others reveal very high rates of default. The different repayment dynamics between the deadline and end of the monitoring period⁴¹ suggest that the local authorities, who were asked to support our encashment activities at the end of the deadline (see Section 1.6.1), put different levels of effort into enforcing the payments, thereby inducing heterogeneous incentives to pay.

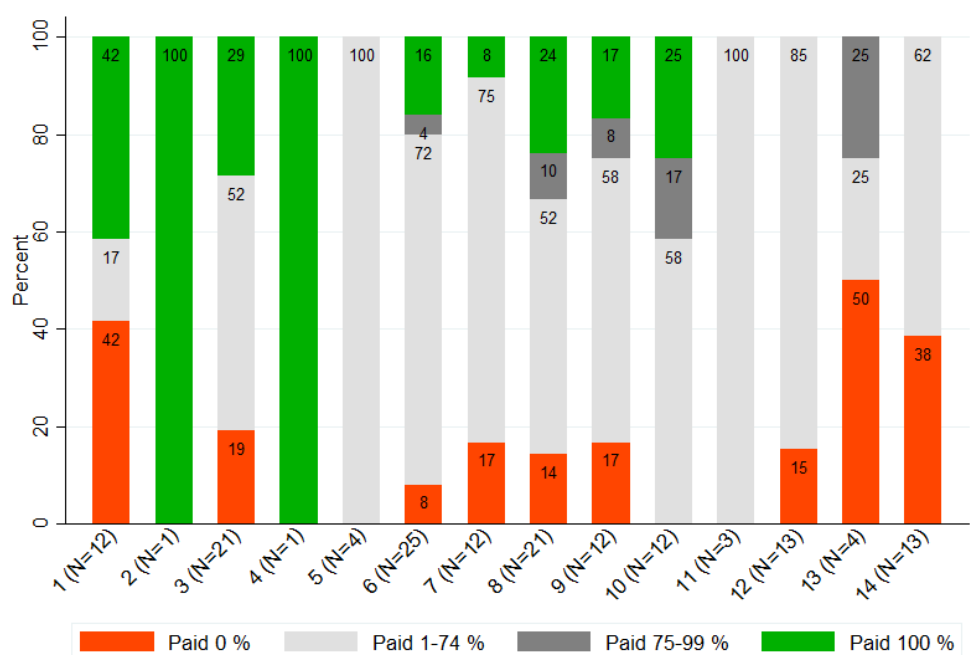
⁴¹ In one community the full payment share raises from 0 to 100 between deadline and monitoring end (community 5), and in three communities it increases by more than 60 percentage points (communities 3, 6, and 7).

Figure 1C.1: Share of final price paid for all kits, by community

Panel A: By end of monitoring



Panel B: By end of deadline



Note: Own illustration. Only 14 out of 16 communities are displayed as no sales were closed in two communities.

Appendix 1D: Decline and default – Robustness of the effect of relaxing liquidity constraints

In the main chapter (Section 1.6), we assess the robustness of our conclusions on the effect of relaxing liquidity constraints regarding decliners and defaulters. We re-run our analysis from Table 1.4 regressing the households' bid on the payment schemes, and control for declining and defaulting. We now include in the regression a decliner dummy and control for defaulting by including the share of the original bid that the household effectively paid. For non-winners, we predict hypothetical declination and defaulting also based on the payment schemes, because we can see in Appendix 1B that declining is particularly driven by the payment schemes. However, this entails multicollinearity between these variables on the right-hand side and makes a clear interpretation of the coefficients difficult. Therefore, we perform two additional robustness checks that consistently show that accounting for decliners and defaulters does not alter our results.

First, we predict hypothetical defaulting and declining without the payment schemes, using only the information on the favorite kit, the bid, the price drawn at the village level, and our full set of control variables. This approach predicts very similar hypothetical behavior of non-winners and, as to be expected, overall results do not change substantially (see Table 1D.1, column (3) and (7)). Second, we assume that non-winners do not default and do not decline. Accordingly, the declining dummy is set 0 for all non-winners and the share paid is set to 100. Again, results do not change substantially (see Table 1D.1, column (4) and (8)).

Table 1D.1: Payment periods and WTP (controlling for defaulting and declining)

	(1) Kit1	(2) Kit1	(3) Kit1	(4) Kit1	(5) Kit2	(6) Kit2	(7) Kit2	(8) Kit2
	Original	Adjusted	Predicted without payment scheme	Non- winners don't default/de cline	Origin al	Adjusted	Predicted without payment scheme	Non- winners don't default/de cline
Six weeks	0.014 (0.808)	0.020 (0.713)	0.015 (0.786)	0.019 (0.726)	-0.009 (0.898)	-0.027 (0.687)	-0.003 (0.961)	-0.007 (0.920)
Five months	0.120 (0.037)*	0.140 (0.014)**	0.115 (0.042)**	0.126 (0.027)**	0.070 (0.298)	0.055 (0.403)	0.071 (0.275)	0.089 (0.200)
HH defaulted (share paid)		-0.002 (0.186)	-0.003 (0.130)	-0.002 (0.157)		0.007 (0.000)***	0.007 (0.000)***	-0.004 (0.000)***
HH declined =1		0.344 (0.000)***	0.332 (0.000)***	0.385 (0.000)***		0.130 (0.342)	0.125 (0.353)	0.428 (0.002)***
N	323	323	323	323	323	323	323	323
<i>Control variables</i>								
Community and Time	YES	YES	YES	YES	YES	YES	YES	YES
Socio-economic characteristics	YES	YES	YES	YES	YES	YES	YES	YES
Baseline energy consumption	YES	YES	YES	YES	YES	YES	YES	YES

Appendix 1E: Amortization periods

Given that the smaller kits (i.e., Kits 1 and 2) will not replace energy costs completely, we use a ‘replacement factor’ (RF, derived from Grimm et al. 2017) that approximates the share of expenditures on kerosene, dry-cell batteries, and candles to be effectively replaced by the solar kits. We assume that Kits 1 and 2 will replace approximately 75 percent of lighting expenditures (see Table 1E.1). Kit 2 further replaces 75 percent of radio and all phone charging expenditures. Kit 3 replaces all traditional energy sources in these categories. Based on these assumptions, Table 1E.1 shows that the amortization periods for the three kits are on average 29, 37, and 144 months. Note that, according to the expected lifetime that *Dassy* communicates to customers, Kit 3, unlike Kit 1 and Kit 2, would (on average) amortize only after the end of its lifespan (see Section 1.3.1).

Table 1E.1: Savings potential of solar kits

Kit	Average replaceable energy expenditures in USD on... * RF					Total monthly savings (in USD)	Amortization (in months)
	...phone charging	...candles	...batteries for lighting	...kerosene for lighting	...batteries for radio		
1	1.11 * 0.00	0.16 * 0.75	0.62 * 0.75	0.35 * 0.75	0.25 * 0.00	0.84	30
2	1.11 * 1.00	0.16 * 0.75	0.62 * 0.75	0.35 * 0.75	0.25 * 0.75	2.13	37
3	1.11 * 1.00	0.16 * 1.00	0.62 * 1.00	0.35 * 1.00	0.25 * 1.00	2.47	144

Sources: RF abbreviates replacement factor. Expenditures data from own data set. Note that we use average amortization periods here. Because of outliers, averaging replaceable expenditures first leads to shorter periods (15, 18, and 73 months).

Appendix 1F: Main regression results

Regression results including control variables are depicted in Table 1F.1 and Table 1F.2. The control variable coefficients in Table 1F.1 show that there is a correlation between the gender of the respondent and the WTP (for Kit 2, for example, female respondents are associated with an 18 percent decrease in their bids). The share of school-aged children within households is a positive correlate (a 10 percent higher kids' share is associated with a two percent increase in the bid) and mobile phone charging expenditures are positively correlated for Kit 2 but not for Kit 1, which is intuitive since Kit 1 does not have a charging port. A one USD increase in monthly phone charging expenditures is associated with an eight percent, i.e., 1.16 USD, increase in the bid for Kit 2.

Table 1F.1: Detailed regression results of Table 5 - Payment periods and WTP

	Kit1				Kit 2		Kit 3		
<i>Payment periods</i>									
Six weeks	0.022 (0.698)	0.009 (0.868)	0.014 (0.808)	0.016 (0.821)	-0.008 (0.911)	-0.009 (0.898)	0.108 (0.415)	0.088 (0.499)	0.058 (0.649)
Five months	0.127 (0.024)**	0.128 (0.025)**	0.120 (0.037)**	0.087 (0.214)	0.090 (0.193)	0.070 (0.298)	0.075 (0.560)	0.073 (0.574)	0.042 (0.743)
<i>Socio-economic characteristics</i>									
Female respondent		-0.056 (0.231)	-0.048 (0.302)		-0.177 (0.003)***	-0.180 (0.002)***		-0.216 (0.036)**	-0.189 (0.059)*
HoHs years of education		0.009 (0.268)	0.009 (0.282)		0.020 (0.021)**	0.017 (0.044)**		0.027 (0.063)*	0.025 (0.076)*
HH size		-0.028 (0.082)*	-0.028 (0.079)*		-0.018 (0.384)	-0.019 (0.351)		-0.013 (0.729)	-0.011 (0.769)
HoH is a farmer		0.065 (0.288)	0.064 (0.309)		-0.085 (0.202)	-0.058 (0.385)		0.060 (0.641)	0.155 (0.247)
Share of students in HH		0.002 (0.085)*	0.002 (0.164)		0.002 (0.120)	0.003 (0.064)*		0.003 (0.206)	0.003 (0.173)
House with tile roofing		0.193 (0.060)*	0.170 (0.103)		0.130 (0.292)	0.053 (0.670)		-0.145 (0.428)	-0.168 (0.370)
Monthly non-energy expenditures (USD) ^{1,2}		0.000 (0.469)	0.000 (0.447)		0.001 (0.037)**	0.000 (0.358)		-0.000 (0.808)	-0.001 (0.318)

...

Table 1F.1 continued

Table 11.11 Continued

	Kit1				Kit 2			Kit 3	
<i>Baseline energy consumption</i>									
Monthly phone charging expenditures (USD) ¹			0.014 (0.529)			0.075 (0.004)***			0.048 (0.236)
Monthly energy expenditures (USD) ^{1,3}			-0.014 (0.261)			0.007 (0.628)			0.061 (0.006)***
Ownership of car battery			0.127 (0.412)			0.164 (0.266)			0.302 (0.090)*
Ownership of rechargeable lamp			0.171 (0.052)*			0.048 (0.612)			0.086 (0.639)
Ownership of solar lights			-0.018 (0.844)			-0.239 (0.013)**			-0.153 (0.398)
Constant	1.178 (0.000)***	1.014 (0.000)***	-0.953 (0.000)***	-0.749 (0.000)***	-0.794 (0.000)***	-0.825 (0.000)***	3.774 (0.000)***	3.836 (0.000)***	3.672 (0.000)***
N	323	323	323	323	323	323	323	323	323
Mean WTP of one-week payment group (in USD)	4.50	4.50	4.51	15.46	15.43	15.44	70.87	70.58	77.67
<i>Control variables</i>									
Community and time	YES	YES	YES	YES	YES	YES	YES	YES	YES
Socio-economic characteristics	NO	YES	YES	NO	YES	YES	NO	YES	YES
Baseline energy consumption	NO	NO	YES	NO	NO	YES	NO	NO	YES

*Note: p-values are displayed in parentheses, where *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ denote statistical significance. We display coefficients from an IR estimation with robust standard errors. The dependent variable is log of WTP. The base category is a one-week payment period. ¹ The values are bottom and top coded at two percent and 98 percent of the distribution, respectively, to eliminate the effects of outliers. ² Excluding energy and phone charging expenditures. ³ Including expenditures on kerosene, gas, batteries, candles and charcoal; excluding expenditures on wood and rechargeable lamp charging.*

Table 1F.2: Detailed regression results of Table 5 restricted to sample without access to modern electricity - Payment periods and WTP

	Kit1			Kit 2			Kit 3		
<i>Payment periods</i>									
Payment period: 6 weeks	0.026 (0.670)	0.008 (0.890)	0.014 (0.819)	0.023 (0.760)	0.009 (0.905)	0.009 (0.898)	0.088 (0.532)	0.075 (0.577)	0.074 (0.572)
Payment period: 5 months	0.138 (0.016)**	0.130 (0.024)**	0.128 (0.028)**	0.110 (0.132)	0.104 (0.150)	0.087 (0.220)	0.142 (0.276)	0.138 (0.292)	0.107 (0.403)
<i>Socio-economic characteristics</i>									
Female respondent		-0.076 (0.121)	-0.069 (0.159)		-0.193 (0.002)***	-0.200 (0.001)***		-0.157 (0.160)	-0.144 (0.186)
HoH's years of education		0.008 (0.361)	0.008 (0.375)		0.020 (0.029)**	0.016 (0.073)*		0.026 (0.091)*	0.024 (0.114)
HH size		-0.036 (0.039)**	-0.035 (0.043)**		-0.029 (0.217)	-0.040 (0.074)*		-0.008 (0.843)	-0.020 (0.628)
HoH is a farmer		0.094 (0.166)	0.091 (0.178)		-0.087 (0.237)	-0.043 (0.557)		0.210 (0.145)	0.286 (0.046)**
Share of students in household		0.002 (0.053)*	0.002 (0.113)		0.003 (0.101)	0.003 (0.068)*		0.002 (0.394)	0.003 (0.343)
House with tile roofing		0.133 (0.229)	0.115 (0.310)		0.119 (0.415)	0.083 (0.570)		-0.031 (0.889)	-0.008 (0.972)
Monthly non-energy expenditures (USD) 1,2		0.000 (0.356)	0.000 (0.309)		0.001 (0.044)**	0.000 (0.526)		-0.000 (0.831)	-0.001 (0.196)
<i>Baseline energy consumption</i>									
Monthly phone charging expenditures (USD) ¹			0.010 (0.657)			0.086 (0.002)***			0.084 (0.055)*
Monthly energy expenditures (USD) ^{1,3}			-0.021 (0.148)			0.010 (0.492)			0.059 (0.025)**
Ownership of car battery									
Ownership of rechargeable lamp			0.190 (0.047)**			0.065 (0.546)			0.204 (0.308)
Ownership of solar lights									

...

Table 1F.2 continued

	Kit1				Kit 2		Kit 3		
Constant	-0.940 (0.000)***	1.082 (0.000)***	-0.969 (0.000)***	-0.759 (0.000)***	-0.803 (0.000)***	-0.825 (0.000)***	3.759 (0.000)***	-0.386 (0.000)***	3.384 (0.000)***
N	287	287	287	287	287	287	287	287	287
<i>Control variables</i>									
Community and time	YES	YES	YES	YES	YES	YES	YES	YES	YES
Socio-economic characteristics	NO	YES	YES	NO	YES	YES	NO	YES	YES
Baseline energy consumption	NO	NO	YES	NO	NO	YES	NO	NO	YES

*Note: p-values are displayed in parentheses, where *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ denote statistical significance. We display coefficients from an IR estimation with robust standard errors. The dependent variable is log of WTP. The base category is a one-week payment period. ¹ The values are bottom and top coded at two percent and 98 percent of the distribution, respectively, to eliminate the effects of outliers. ² Excluding energy and phone charging expenditures. ³ Including expenditures on kerosene, gas, batteries, candles and charcoal; excluding expenditures on wood and rechargeable lamp charging.*

Appendix 1G: Learning and WTP

Table 1G.1: Summary statistics on pre-experiment solar kit exposure

	Mean
No kit exposure	0.13
Positive word-of-mouth	0.64
Negative/undefined word-of-mouth	0.01
Usage elsewhere	0.09
Negative ownership experience	0.01
Positive/undefined ownership experience	0.03
Current ownership	0.09
N	323

Note: The experience proxies are displayed in increasing order, from lowest to highest possible exposure. Households are coded as their highest exposure, i.e., a participant with current solar kit ownership who also heard about solar kits by word-of-mouth is coded as the former.

Table 1G.1 reports the highest level of exposure to solar kits of bidding game participants prior to our bidding game. In total, 13 percent have had no exposure at all. Most participants had only heard about solar kits somewhere (65 percent), with virtually all the word-of-mouth being positive. 10 percent had used a solar kit elsewhere, for example at a market or a neighbor's house. Almost five percent of households had previously owned a solar kit, and one third of those households described their experience as negative. Nine percent of participants owned a solar kit at the time of the bidding game.

Our main analysis takes a static perspective in that it cannot assess how WTP for solar technologies will change once personal experience, social learning, and peer effects set in. In Table 1G.2 we use the exposure variables from above as proxies for previous learning about solar kits. Note that these learning proxies are endogenous, and our interpretation is hence purely correlative. The results are in line with expectations. The coefficients that stand out most in terms of economic and statistical significance show that households with negative previous experiences have a lower WTP for Kit 1, today.

Table 1G.2: Payment periods, WTP and former solar kit exposure

	Kit1	Kit2
Payment period: 6 weeks	0.026 (0.667)	0.017 (0.812)
Payment period: 5 months	0.120 (0.040)**	0.067 (0.346)
Positive word-of-mouth	0.058 (0.472)	0.190 (0.074)*
Negative word-of-mouth	-0.028 (0.934)	0.015 (0.945)
Usage elsewhere	0.117 (0.252)	0.216 (0.076)*
Negative ownership experience	-0.432 (0.007)***	-0.200 (0.319)
Positive/undefined ownership experience	-0.094 (0.552)	0.212 (0.122)
Constant	0.968 (0.000)***	2.405 (0.000)***
N	294	294
<i>Control variables</i>		
Community and Time	YES	YES
Socio-economic characteristics	YES	YES
Baseline energy consumption	YES	YES

*Note: p-values are displayed in parentheses, where *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ denote statistical significance. We display coefficients from an IR estimation with robust standard errors. The dependent variable is log of WTP. The base category for payment period is a one-week payment period, and the base category for the exposure proxies is no exposure. We exclude households that currently own a solar kit, as the drivers of WTP for a second solar kit are presumably different. We do not run the regression for Kit 3 as former experience with solar kits virtually completely involved only small devices comparable to Kit 1 and 2.*

2 The supply side of technology diffusion – Evidence from rural Senegal.

With Marc Jeuland, Ousmane Ndiaye, Jörg Peters, Maximiliane Sievert and Faraz Usmani

2.1 Introduction

Diffusion of productivity- and welfare-enhancing technologies drives socio-economic development at the macro level (Solow 1956, Comin and Hobijn 2010, Caselli and Coleman 2001, Keller 2004). At the micro scale, a wide range of technologies is expected to be profitable for entrepreneurs, to increase welfare of end-users, or to protect the global commons. Yet, technologies often diffuse slowly at best, especially in so-called Bottom-of-the-economic-Pyramid (BoP) markets in the Global South. Considerable research has examined demand-side approaches to increasing the uptake and sustained use of beneficial technologies (see Foster and Rosenzweig 2010 for a review). Yet, technology diffusion is not only a demand, but also a supply-side process, and supply-side constraints that restrict technology accessibility in BoP markets remain poorly understood.

In this chapter, we use a randomized controlled trial (RCT) to assess how the relaxation of supply-side constraints among vendors facilitates the establishment of self-sustaining markets for beneficial technologies in rural settings. We study this in the context of markets for improved cookstoves (ICS) in Senegal. To do so, we surveyed all main nodes of the ICS market, covering producers, intermediary vendors in rural markets, and end-users in villages.

ICS can generate benefits for people's health and time use, local forests, and the global climate if they replace traditional stoves that are often simply composed of three stones.⁴² Traditional stoves and solid fuels are currently used by nearly three billion people globally (IEA et al. 2020), providing large potentials for welfare improvement. In Senegal, 86 percent of the rural

⁴² Cooking with traditional stoves generates health and productivity costs and causes serious environmental damages at regional and global scales (Anenberg et al. 2013, Lim et al. 2013). Household air pollution produced by dirty fuels is a major health threat, especially to women and children, and is estimated to cause four million annual premature deaths and five percent of the global burden of disease (Smith et al. 2014). Solid fuel usage contributes to deforestation and a loss of carbon sinks (Bailis et al. 2015) and its combustion generates substantial climate-forcing emissions (Ramanathan and Carmichael 2008, Shindell et al. 2012). For reviews of the impacts of improved stoves, see for example Mehetre et al. (2017) and Thakur et al. (2018). Net benefits of the technology to households can however also be negative (Jeuland and Pattanayak 2012) and can vary between laboratory tests and real-world conditions (Wathore et al. 2017).

population uses firewood to meet its primary energy needs (WFP 2017). To lower the resulting adverse effects, the Senegalese government promotes a simple and low-cost ICS called firewood *Jambar*. Prior research has both shown that the firewood *Jambar* can lower households' firewood consumption (Bensch and Peters 2015), and that rural households' willingness to pay (WTP) for the stove substantially exceeds its urban market price (Bensch and Peters 2020). Puzzlingly, uptake of the firewood *Jambar* in rural areas, where households typically rely on self-collected firewood, remains nevertheless low. In contrast, the charcoal *Jambar*, the stove variant that is usually used by more urban or wealthier households, is sold in higher quantities.

We hypothesize that this conundrum of under-adoption can partly be explained by weak rural supply chains that limit accessibility of the *Jambar* in rural settings. To test this hypothesis, we experimentally relax informational, marketing input, and financial constraints that may prevent informal vendors in weekly rural markets from offering the firewood *Jambar* among their wares. The weekly markets, known as *loumas*, are the “late-mile” locations connecting rural demand to urban supply. Specifically, we sampled 60 *loumas* and randomly assigned a sample of 127 *louma* vendors operating in these *loumas* to a pure control arm and two treatment arms. While small in absolute terms, this sample comprises more than half of Senegal's administrative regions (and by far the most densely populated ones), over 40 percent of all *loumas* within these regions, and 58 percent of all existing kitchenware vendors within the *loumas*. Vendors assigned to the information-marketing (IM) treatment receive information on local WTP, contact information of producers, a sample of two *Jambar* ICS, and marketing materials. Vendors assigned to the information-marketing-grant (IMG) treatment receive the IM treatment as well as a one-time USD 31 cash grant labelled unconditionally for *Jambar* transport, for example, to villages or *loumas*. To quantify the local WTP and then share it with vendors as part of the two treatments, we conducted incentive-compatible, second-price auctions for the device among over 900 individuals in 60 nearby villages.

This chapter thereby puts forth a technology diffusion approach that relies on an established “late-mile” supply chain. Over the last two decades, the private sector, governments, non-profit and international organizations have pioneered a range of alternative business models to boost ICS diffusion across the Global South. These initiatives include the creation of new ICS-specific delivery channels, engagement of village-level entrepreneurs or other grassroots sales agents, and partnerships with stores, schools, village-based organizations, and micro-finance

institutions.^{43,44} One such example is the micro-consignment model (Van Kirk 2010).⁴⁵ The treatment we provide is inspired by such supply-side approaches, but re-focuses on an established supply chain that traditionally caters products to remote populations. Importantly, our intervention also builds on materials tested and used by the Senegalese national ICS programme.

Using monthly mobile phone surveys spanning a period of nearly two years around the intervention, we track vendors' sales of the firewood *Jambar* and of other stove types. Moreover, we measure long-term impacts on sales two years after the intervention in an additional survey wave. Similar sales surveys conducted with 215 producers of the firewood *Jambar* allow us to track upstream effects. Our analyses thus capture all key actors in the ICS market: rural end-users from 60 villages who participated in demand surveys, intermediary vendors, and upstream producers.

Despite growing recognition of the potential importance of stable supply chains for diffusion and sustained use of ICS (e.g., Lewis et al. 2015, Pattanayak et al. 2016, GACC and enea 2018) and some evidence on the production and delivery of clean input fuels (e.g., Puzzolo et al. 2019), empirical evidence on supply-side barriers to ICS diffusion is largely absent. The only exception shows that a combination of supply and demand promotion stimulates adoption of ICS in India (Pattanayak et al. 2019). Previous empirical evidence on supply-side barriers to the diffusion of other technologies in rural areas is also scant and has almost exclusively focused on capital goods for agricultural production (e.g., Minten et al. 2013, Aggarwal et al. 2018, Suri 2011). To the best of our knowledge, the only exception shows that credit provided to solar lamp vendors in Uganda increases their sales (Fuchs et al. 2020).

A large and related literature deals with the establishment of well-functioning and integrated markets in the Global South, not for technologies, but for agricultural and aquacultural produce such as maize, cocoa, or fish. First, there is evidence both for well-functioning, competitive and uncompetitive markets. Uncompetitive markets are characterized by trader collusion, low-price pass-through rates to remote farmers (Bergquist and Dinerstein 2020, Osborne 2005), and

⁴³ See for example the analysis of 10 distribution initiatives of ICS by SNV, Practical Action Consulting and the Alliance: SNV (2015).

⁴⁴ Supply-side models are often combined with demand-side approaches to enhance adoption, such as pay-as-you-go payment solutions using smart meter technologies (see Envirofit, <https://envirofit.org>) or – for more advanced stoves – “tool and fuel” business models that combine sales of stoves with their associated fuels (see e.g., Inyenyeri in Rwanda, <http://www.inyenyeri.org/>).

⁴⁵ The micro-consignment provides individuals with training, products, and information necessary to market products, specifically in rural areas.

constant returns to scale (Fafchamps et al. 2005). Competitive markets include cocoa markets with high subsidy pass-through rates from traders to farmers (Casaburi and Reed 2020), and spatially integrated rice markets (Moser et al. 2009). Second, a set of papers studies the impact of reducing price information frictions among middlemen or producers, again in primary product markets. At the middlemen level, reduced informational search costs (Aker 2010, Allen 2014, Jensen 2007), and non-price information frictions related to quality and trust (Arimoto et al. 2019) decrease price dispersion. At the producer level, price information increases the prices they receive (Goyal 2010, Svensson and Yanagizawa 2009), or provides them access to higher-quality inputs in some settings (Jensen and Miller 2018), yet again not in others (Fafchamps and Minten, 2012, Mitra et al. 2018).

We find that vendors randomly assigned to the IMG treatment sold approximately 0.9 more firewood *Jambars* per month following the intervention. This is a significant effect compared to 0.08 stoves sold on average in the pre-intervention months. This effect is small in absolute, but large in relative terms, increasing sales by over 1000 percent. In contrast, we find no discernible impact of the IM treatment on stove sales. Taken together, our research design allows us to identify that informational and marketing support are only effective if combined with financial support. As a potential mechanism behind these increased sales, we find that IMG vendors expanded their marketing activities more than control vendors and somewhat more than IM vendors. Importantly, we show that these effects remain in the long-run two years after the intervention despite market disruptions from COVID-19 policies.

We find no consistent evidence for differential effects of the intervention along key pre-specified vendor and business dimensions, such as business size. However, we descriptively show large heterogeneity in impact across regions and individual vendors, and qualitatively discuss some characteristics that may have acted as catalyzers. These findings show that context and targeting are crucial and are broadly in line with the evidence on informal sector heterogeneity (e.g., Grimm et al. 2012, Cunningham and Maloney 2001), as well as with evidence on microfinance showing that some businesspersons better transform (financial) support into business growth than others (e.g., Meager 2019, Fiala, 2018, De Mel et al. 2008). Lastly, we show that increases in sales vary across months, which is roughly in line with the typical seasonality of sales in *loumas*, driven by seasonal income, climate, and occurrence of (religious) festivities.

However, increased sales of *louma* vendors do not translate into detectable increases in sales reported by upstream producers. This is not surprising given that the additional firewood

Jambars sold by vendors constitute a small share of producers' nationwide sales, and that producers' sales are trending downward in the years of our experiment.

Lastly, we show that our IMG intervention provokes cross-product externalities, as it also affects the vendors' sales of other ICS types, thereby generating important co-benefits. While conceptually possible, we do not find negative nor positive effects on vendors' sales of traditional stoves. Yet, we anyhow underline that an approach targeting the private sector to boost technology diffusion needs to manage incentives very carefully, as it in theory may as a side effect enhance sales of products that are detrimental on a societal or environmental level.

Taken together, our intervention provides innovative evidence on the potential of supply-side policy tools targeting established market actors to meet latent demand for welfare-improving technologies, such as ICS, in rural settings. In this sense, while effect sizes suggest that additional (demand-side) interventions are required to boost large-scale diffusion of the stove, the present study is a successful proof-of-concept. More evidence is needed to determine if more sophisticated welfare-improving technologies (or those unknown in local contexts) can be promoted in similar ways.

The analyses follow a pre-analysis plan (PAP) registered with RIDIE (RIDIE-STUDY-ID-59c9e0f49a591). The most relevant deviations from this plan are that we (i) prolonged data collection and accordingly added an analysis of long-term impacts, (ii) added additional tests for robustness of results, and (iii) treat missing dependent variables differently than pre-specified due to the nature of the missing data. Any deviation from the PAP and the underlying reasons are listed in Appendix Table 2A.1.

This chapter is structured as follows: Section 2.2 discusses the intervention, Section 2.3 its underlying conceptual rationale, and Section 2.4 presents our experiment and data, including surveys, sampling, and balancing. Section 2.5 discusses the Senegalese *Jambar* market. Section 2.6 presents the empirical approach, and Section 2.7 summarizes treatment uptake, and discusses all impact estimates, including tests for robustness and heterogeneity, impacts on secondary outcomes, and cost-effectiveness of the intervention. Section 2.8 concludes.

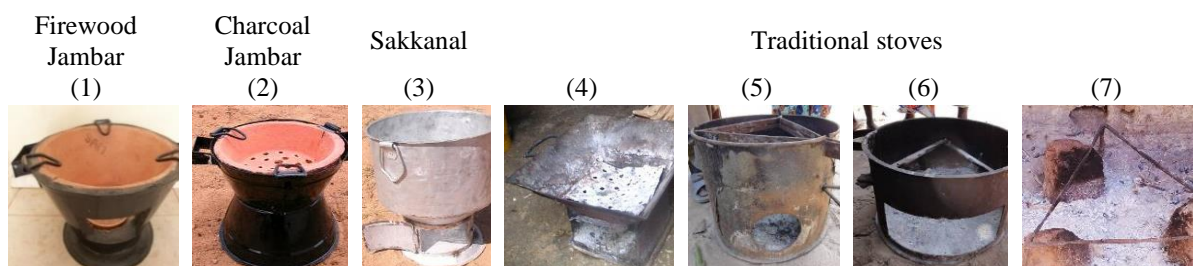
2.2 Intervention

As part of its national FASEN (*Foyers Améliorés au Sénégal*) cookstove programme, the government of Senegal has since 2007 trained artisans to produce and market the *Jambar* ICS, aiming to establish a self-sustaining market for the stove. The *Jambar* is a simple and low-cost biomass stove that comes in charcoal and firewood variants (Figure 2.1, stoves (1) and (2)) in

three different sizes that cater to different cooking needs and pot sizes.⁴⁶ As a complement to promoting the *Jambar* supply side, the FASEN programme has also selectively targeted the *Jambar* demand side via awareness raising campaigns⁴⁷ in some rural areas.

According to FASEN’s monitoring data, the FASEN-trained producers have since 2007 sold over 1.4 million *Jambar* cookstoves. Yet this success largely stems from the charcoal variant (76 percent of all sales) that is predominantly used in urban and peri-urban areas where households (can) afford purchasing charcoal⁴⁸. Hence, despite evidence that suggests rural households’ WTP for the device exceeds its urban market price (Bensch and Peters 2020), diffusion in rural areas, where end-users typically rely on self-collected firewood, remains low.

Figure 2.1: Main stove types offered in loumas



Note: Traditional stoves include (from left to right): *Malgache*, *Bili*, *Bili amélioré*, *Nopale*.

Figure 2.1 shows all main stove types for sale in surveyed *loumas*, where stoves (1)-(3) are simple ICS, all manufactured by FASEN-trained producers. The ICS differ mostly by the fuel type they require (the *Sakkanal* runs both on charcoal and firewood) and hence their usability in rural and urban areas. Fuel feed, height, and tripod of the simple ICS are designed to use fuel more efficiently than traditional stoves. Stoves (4)-(7) are such basic, traditional stoves, of which the latter (7) is commonly used. FASEN producers also produce variants hereof: their production requires similar materials and tools and targets similar markets. Supply of very advanced (i.e., gasifier or electric) stoves in these *loumas* is very rare, if not inexistent.

⁴⁶ The *Jambar* comprises a metal cylinder and a clay inlay and is designed primarily to curb biomass fuel consumption. In a controlled laboratory setting, we tested the *Jambar* together with our local partner, the Centre d’Études et de Recherches sur les Énergies Renouvelables (CERER). The *Jambar* was found to have higher thermal efficiency during high-intensity cooking sessions relative to a traditional “three-stone” stove, while consuming similar amounts of fuel during low-intensity cooking.

⁴⁷ The activities include village-level TV and radio campaigns, cooking demonstrations, contests, and distribution of printed materials such as flyers, posters, road signs and T-shirts.

⁴⁸ According to Demographic and Health Surveys (DHS) data, using data collected between 2014 and 2017, 81 percent of rural Senegalese households used firewood as their main cooking fuel, and 9 percent charcoal. Among urban households, 30 percent each relied on firewood and charcoal. These numbers are even slightly more pronounced when taking the average across 31 sub-Saharan African countries. See DHS (2021). Available Datasets, <https://dhsprogram.com/data/available-datasets.cfm>.

Our intervention extends FASEN’s producer-level activities to intermediaries operating in peri-urban and rural areas. Our intervention targets vendors who already sell ICS or other closely related goods (such as pots, kitchenware, traditional stoves, and sometimes charcoal *Jambars*) in weekly markets known as *loumas*.

All intervention elements were delivered during a one-time, one-to-one, in-person visit with vendors in *loumas* where we explained the purpose and deployment of each element. Table 2.1 provides an overview of the various intervention elements delivered to treatment vendors (see Appendix 2B for details). The demand leaflet conveys households’ WTP for the firewood *Jambar* in seven villages. The information is derived from auctions we conducted prior to the intervention among over 900 households in 60 randomly selected villages nearby the *loumas*. As each vendor operates in a unique set of *loumas*, each vendor receives a customized sheet that refers to the seven villages surrounding a *louma* in which s/he operates. For each village, the demand leaflet presents the highest village-level WTP, the extrapolated number of households willing to pay more than USD 12.30 (the FASEN-suggested retail price for the firewood *Jambar*), and contact information for village-level authorities. These details are presented visually compellingly to foster intelligibility, particularly by vendors who can read numbers only (Appendix 2B). The demand leaflet thus informs vendors about demand patterns in nearby villages and provides means to engage directly with relevant village-level individuals, thereby reducing uncertainty and downstream search costs in marketing the *Jambar*.

The producer contact leaflet (Appendix 2B) lists the name, telephone number, and location of all 103 FASEN-trained producers who manufacture the firewood variant of the *Jambar*. This information reduces vendors’ upstream search costs related to identifying potential suppliers and shopping around for the lowest prices. The demonstration firewood *Jambars* allow vendors to acquaint themselves with the technology and learn about demand for the stove without incurring investment costs or other risks. We provided basic training on how these ICS could be used during demonstration events with potential customers. The marketing materials include a *Jambar* T-shirt, a marketing poster, and a pamphlet with illustrations of best ways to use the *Jambar*. The materials enable vendors to present the expected benefits of the firewood *Jambar* compellingly, thereby stimulating vendors’ salespersonship and potentially demand of customers.

Lastly, the one-time, transport grant enables IMG vendors to transport firewood *Jambars* to nearby villages or *loumas* for marketing and sales purposes. Although we earmarked the grant for covering transport costs, we neither monitored uses, nor stated to vendors that we would

require any materials for verification.⁴⁹ We provided USD 31 to ensure that the transport grant covers the transportation cost for a higher number of the firewood *Jambar*.⁵⁰

Table 2.1: Intervention elements, by experimental group

Element	Control	IM	IMG
Demand leaflet from WTP survey	X	✓	✓
Leaflet with producer contacts	X	✓	✓
Two firewood <i>Jambars</i>	X	✓	✓
Marketing materials	X	✓	✓
Transport grant (31 USD)	X	X	✓

2.3 Conceptual rationale

The main conceptual rationale underlying our intervention is rooted in transaction cost theory (Williamson 1979), as the intervention aims to reduce market failures and resulting inefficiencies. More concretely, our intervention aims to reduce transaction costs in a context of imperfect information, including search, information, bargaining, and decision costs.

We hence hypothesize that access to information, marketing inputs, and financial resources reduces the risk and cost inherent to experimenting with selling a new technology. Low-risk experimentation leads vendors to identify profit-making opportunities conditional on the existence of latent demand and profitability in marketing the stove from the vendors' perspective. This, in turn, will increase sales and hence diffusion of the technology. These increased sales will ultimately crowd-out other stove types. Finally, this generates positive social and environmental welfare effects if the new ICS substitutes for or complements an inferior household stove, i.e., a technology that consumes more fuel, pollutes more, has a lower price-performance ratio, or is less convenient or safe to use.

Figure 2.2 shows the stylized causal chain in more detail, for example also displaying how the intervention can not only cater to existent demand, but also trigger new demand. Yet, it abstracts

⁴⁹ Our field team conveyed that the grant is labelled for transportation purposes as following: “We would like to support your ability to go to these villages. We know that often vendors do not have the financial resources to take their products to villages. We would therefore like to give you XOF 18,000 for arranging transport, which you can use to bring improved stoves to near-by villages and present it to households. If you are successful, you can use your revenues and go to even more villages.”

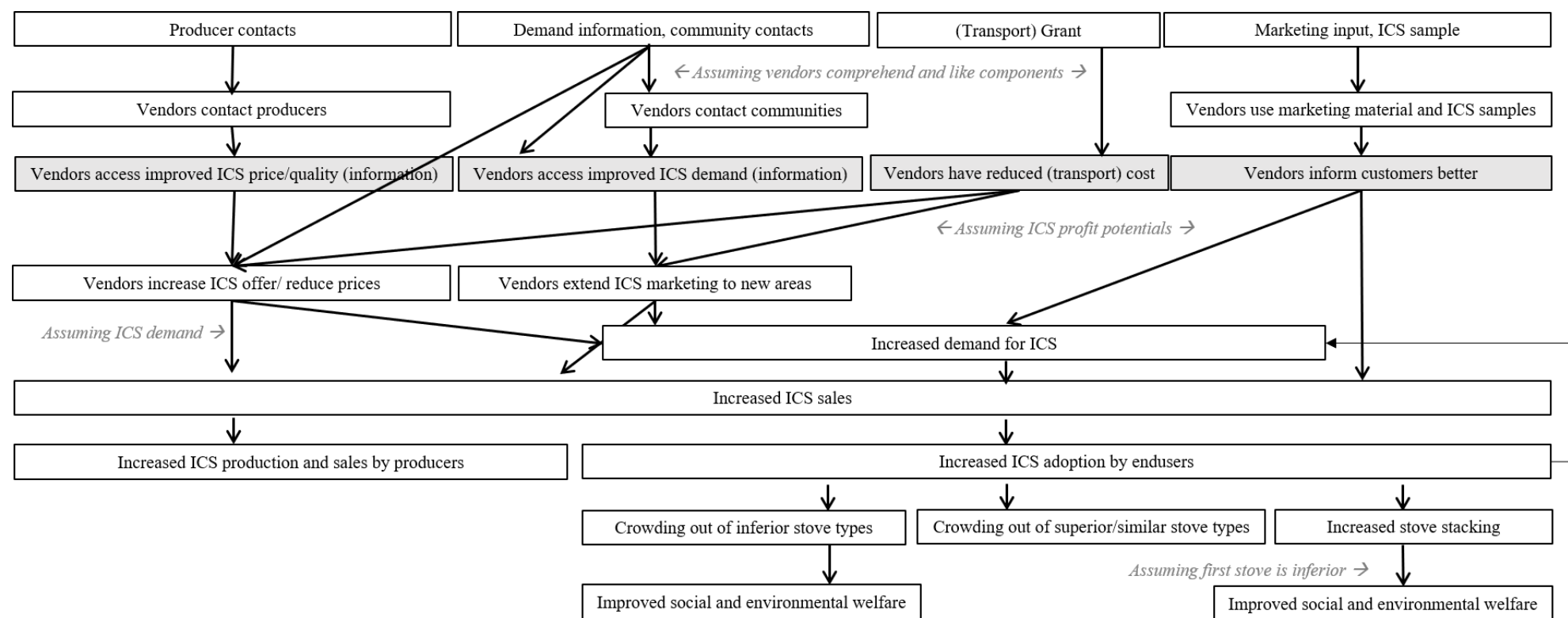
⁵⁰ We based the grant amount on data from our baseline interview, where we surveyed vendors about the costs they would face for transporting ICS to locations at different distances. We found that the reported cost for transporting one single ICS to a location located between 10 and 20 km away is on average USD 2.70 across different transport modes.

from impacts on (treated and untreated) vendor and producer businesses, and second-round effects, for example on prices, competition, and households.

The choice of the single elements was based on (i) consultations with local (FASEN) experts, (ii) inquiry about business barriers in the vendor and producer baseline surveys, (iii) grass-root dissemination approaches put forward by private, non-profit, and international organizations, and (iv) the existing applied micro-economic evidence.

We specify the latter. Each of the elements individually relates to a literature strand. First, our IM and IMG intervention reduce search costs in identifying producers and consumers, which has shown to improve outcomes in agricultural and aquacultural trade (see above, Aker 2010, Allen 2014, Jensen 2007). Second, our grant treatment reduces liquidity constraints, which can inhibit profitable investments (Van Rooyen et al. 2012, De Mel et al., 2008, 2011, 2012; Fafchamps et al. 2014, McKenzie and Woodruff 2008, Karlan and Zinman 2011). More specifically, the grant is earmarked to reduce the ICS transportation cost, which has improved market outcomes in other settings (Datta 2012, Khandker et al. 2009, Mu and Van de Walle 2011, Brooks and Donovan 2020). Third, our free provision of exemplary firewood *Jambar* also substantially reduces the cost and risk inherent to experimenting with (selling) new technologies (see Foster and Rosenzweig 1995). Fourth, our marketing treatment may support entrepreneurial capacities in better marketing the technology and thereby loosely relates to the literature on business training and entrepreneurship (e.g., McKenzie and Woodruff 2014).

Figure 2.2: Stylized causal chain

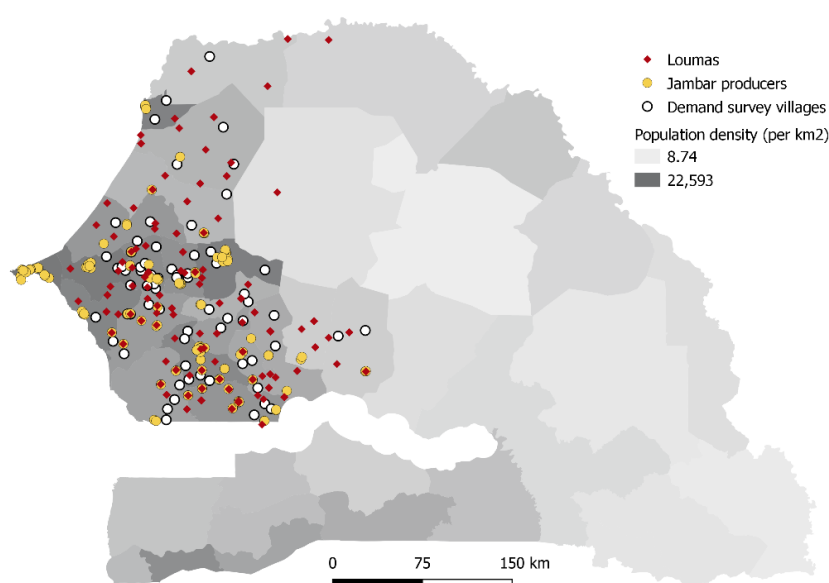


Note: Inferior stoves refer to stoves that consume more fuel, pollute more, have a lower price-performance ratio or are less convenient. Stove stacking refers to the use of multiple stoves by the same cook or household. Does not include impacts on vendor and producer business, nor second round-effect, such as on prices.

2.4 Data

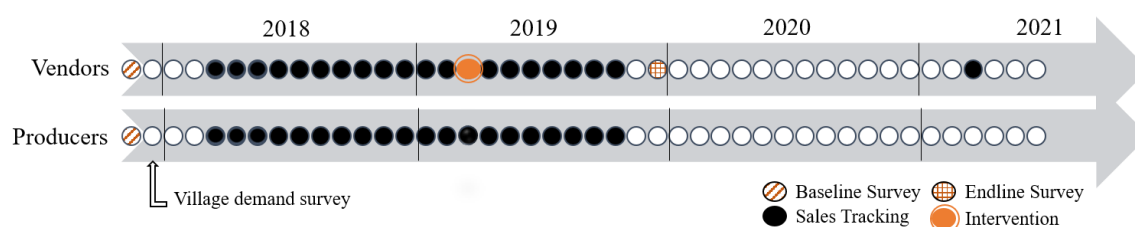
To comprehensively study the market for the firewood *Jambar* in rural Senegal, we combine multiple surveys to cover the three key nodes along the market in eight of Senegal's 14 administrative and most populous regions (Figure 2.3): producers, vendors, and end-users.⁵¹ In total, we surveyed 215 *Jambar* producers in 33 peri-urban and urban localities, 127 intermediary vendors in 60 *loumas*, and 937 potential end-users in 60 rural villages Table 2.2 summarizes the key components of our study, and Figure 2.4 displays the timeline of their roll-out.

Figure 2.3: Survey locations



Source: Own presentation. Population data from the Minnesota Population Center (MPC 2020) based on 2013 census data by the National Agency of Statistics and Demography (ANSD). Areas calculated using QGIS3.

Figure 2.4: Timeline of study components' roll-out



Note: Each circle represents one month.

⁵¹ Our producer-level surveys take place in Dakar, Diourbel, Fatick, Kaffrine, Kaolack, Louga, Saint-Louis and Thiès. Our vendor- and household-level surveys exclude Dakar, the region that encompasses the highly urban national capital and its suburbs. The areas coincide with regions where FASEN has promoted the *Jambar* in the past.

Table 2.2: Study components

Component	Content	Survey mode	Use
Vendor surveys	Baseline and endline surveys in <i>loumas</i>	In-person	Descriptive statistics of vendor businesses; Outcomes in impact analysis
Demand survey	Experimental elicitation of WTP for the firewood Jambar among 937 households in 60 rural villages via sealed-bid, second-price auctions	In-person	Demand information channeled to vendors as key component of the vendor-level intervention
Intervention	Communicates among others the demand survey results	In-person	Assigned randomly to vendors
Vendor tracking	Monthly tracking of vendors' stove sales (all main stove types)	Mobile phone	Outcome in impact analysis
Producer survey	Baseline survey	In-person	Descriptive statistics of producer businesses
Producer tracking	Monthly tracking of producers' firewood Jambar sales	Mobile phone	Outcome in impact analysis

Note: Section 2.4.2. provides details on survey content.

2.4.1 Sampling

To select appropriate study samples for each of our study components, we first focused on the eight regions where FASEN-trained *Jambar* producers are located.⁵² We then selected rural *loumas* located in the same regions as producers, and finally rural villages located near the *loumas*. Our final sample was selected proportional to the density of local markets.

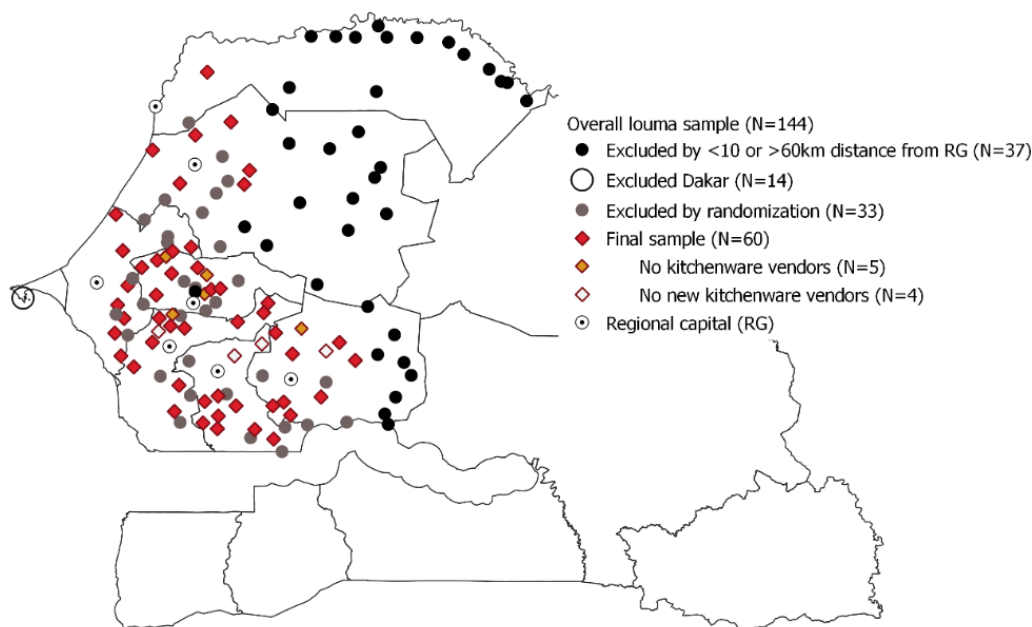
To select *loumas*, we followed a multi-stage approach (see legend Figure 2.5). First, we mapped all 144 regularly held *loumas* in the eight (out of the 14) regions with FASEN-producers.⁵³ Second, we excluded the highly urbanized Dakar region and all 37 *loumas* located less than 10 km or more than 60 km from a regional capital as they either primarily cater to urban customers (who mostly use charcoal-fired stoves) or are very remote raising transaction costs in *Jambar* marketing further. This selection procedure identifies areas to which the technology, being produced in peri-urban areas, would naturally diffuse next. Finally, we randomly selected 60 *loumas* out of the remaining 93 *loumas*, making sure to select at most one *louma* in each *commune* (the Senegalese administrative division immediately above the village level). Note

⁵² This excluded the southern Casamance area of the country where FASEN is not active. This part of Senegal is substantially different from the rest of the country in terms of agro-ecological conditions and availability of firewood. This also excluded eastern Senegal and parts of northern Senegal, which are considerably less populated.

⁵³ We received a list of 144 markets by the Senegalese government, which we verified via mobile phone calls with local authorities.

that apart from the 60 surveyed *loumas*, the surveyed vendors operate in 15 additional *loumas* we did not survey (as they move back and forth between multiple *loumas*).

Figure 2.5: Louma sampling



Note: RG=Regional capital. The radius within 10 and 60km from RGs was constructed using geodetic distance. The map shows 9 markets where either no or no new kitchenware vendors, who had not yet been interviewed on a priorly surveyed market, were present.

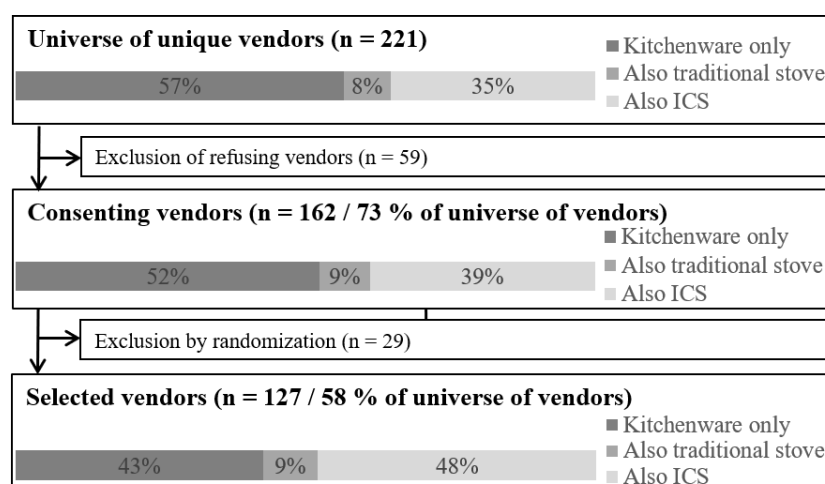
To sample vendors for participation in our survey, in the 60 sample *loumas*, field teams conducted a full listing of all kitchenware vendors, categorizing them into three vendor types: (i) only kitchenware vendors, (ii) also traditional-stove vendors, and (iii) also ICS vendors. The teams identified 221 unique vendors operating within the 60 *loumas*. We asked each of these vendors about their willingness to participate in our study, a total of 59 vendors refused to participate further (Figure 2.6).⁵⁴

From the sample of consenting vendors, we sought to randomly select four vendors in each *louma*.⁵⁵ Field teams selected vendors using a tablet-based randomization tool. If more than four vendors in a particular *louma* consented to participate in our study, the tool prioritized vendors who already sold ICS at baseline over those who sold only traditional stoves, who in turn were prioritized over vendors who only sold kitchenware.

⁵⁴ Refusal is distributed over all three ‘types’ of vendors, but the share of refusers is highest among ICS vendors (18 percent), followed by kitchenware vendors (seven percent), and lastly by traditional stove vendors (two percent). Qualitatively, the most common reason for refusal is that interviews took place during the busy market days, demanding attention from vendors.

⁵⁵ We restricted the number of surveyed vendors to four per *loumas* in the expectation of a much higher number of existing kitchenware vendors.

Figure 2.6: Vendor sampling



The prioritization ensured that the business priorities of sample vendors were broadly aligned with the intervention goal of marketing the firewood *Jambar*, a strategy that also seems reasonable for a scaled-up version of our intervention by policy.

Our final analytical vendor sample consists of 127 vendors or 58 percent of all kitchenware vendors operating in the selected *loumas* (Figure 2.6). Approximately 43 percent of sample vendors sell kitchenware and no stoves at baseline, 9 percent also offer traditional stoves, and 48 percent additionally offer ICS (primarily the charcoal variant of the *Jambar*). Comparing this distribution of vendor types in our analytical sample with the distribution in the universe of vendors shows that our sample-selection strategy oversampled ICS vendors and undersampled kitchenware-only vendors. While the sample covers a large share of existent kitchenware vendors, we hence cannot ensure that it is representative for all kitchenware vendors due to our oversampling strategy and due to participation refusals.

Vendors were assigned to experimental groups after the baseline survey. This random assignment was stratified based on (i) the number of *loumas* the vendor sells in regularly at baseline, and (ii) whether the vendor belonged to a “high” or “low” revenue group (above and below median total monthly revenue) at baseline.

To select firewood *Jambar* producers, we simply sampled the full census of FASEN-trained producers. We managed to survey 215 out of the 228 producers, the remaining producers could not be found despite using contact information from FASEN. The FASEN-trained producers manufacture and sell the *Jambar* stoves predominantly in the capitals of eight Senegalese regions (Figure 2.3).

Lastly, to sample end-users, we randomly selected 60 villages from the census of all Senegalese villages that had a population of between 400 and 1600 people (in 2015) and were located within 30 kms of one of the 60 sampled *loumas*. This was done to elicit demand in areas that were sufficiently large, and reasonably close to sample *loumas*. Approximately 15 households were randomly selected from household rosters within each village and invited to participate in second-price auctions for the firewood *Jambar* stove. In total, 937 households participated in these auctions (see Jeuland et al. 2021 for additional details).

2.4.2 Vendor, producer, and end-user surveys

After a baseline survey covering a large range of business and vendor characteristics (including information on general business characteristics, markets of operation, product range, profits, costs, and customers), we conducted monthly vendor sales tracking via phone calls over a consecutive period of 20 months. Seventeen months later (Figure 2.4), we went back to track sales in an additional month to understand long-term sales developments (discussed separately in section 2.7.6). During the sales tracking survey, we asked vendors to report all stove sales that had occurred since the prior interview. We thereby sought to capture as much of each vendors' stove sales as possible, as we anticipated that vendors would not be reachable or available for interviews every month. During calls, vendors were asked to recall their stove sales, referring to a sales log sheet we had handed out as bookkeeping support whenever wanted.⁵⁶

Table 2.3: Reporting regularity, by experimental group

	(1)	(2)	(3)	(4)	(5)
	Control	IM	IMG	All	ANOVA p-value
Sales report: any month (%)	0.97	0.90	0.96	0.94	0.33
Sales report: any pre-intervention month (%)*	0.97	0.88	0.94	0.92	0.29
Sales report: any post-intervention month (%)*	0.94	0.90	0.96	0.93	0.49
Sales report: mean # of months**	9.10	10.49	10.61	10.18	0.18
Sales report: median # of months**. [°]	10.00	11.00	11.00	10.76	
Endline survey (%)	0.87	0.88	0.92	0.89	0.76
N	31	48	48	127	127

*Note: *includes all calls from the main sales tracking period and the last reporting during in-person endline survey. **conditional on any reporting; °ANOVA is a parametric test and thereby inappropriate to test for differences in medians given the almost equal medians we abstain from adding a non-parametric test.*

⁵⁶ To enhance the quality of monthly sales data (i.e., facilitate self-tracking of sales and ease recall burden), vendors and producers received sales log sheets and were trained to note down their sales on them as a base for mobile phone sales reporting (see Appendix 2C). The log sheets contained both written and graphical instructions to facilitate reading. Survey participants were asked to complete the sheet after each stove sale. Approximately 68 percent of all reported sales were tracked using the log sheets. The remainder were based on recall data.

Participation in the monthly vendor tracking was high overall, with considerable variation over time (see Appendix Figure 2C.3) and across vendors (Appendix Figure 2C.4), but not between experimental groups (Table 2.3, Appendix Figure 2C.3). Overall, 94 percent of vendors report their sales at least during one tracking call. Reporting before and after the intervention varies somewhat but insignificantly across experimental groups (see Table 2.3). Conditional on reporting, the mean and median vendor participated in roughly 10 sales tracking calls.⁵⁷

The endline survey conducted two years after the baseline survey repeated baseline questions and elicited self-reported use of intervention elements. We retained roughly 88 percent of vendors at endline, a rate which varies slightly but insignificantly across experimental groups (Table 2.3).

The producer surveys included in-person baseline interviews, and sales tracking via mobile phone for 20 months using a similar approach as with vendors. The key difference is that we asked producers to report sales only of the firewood *Jambar* to prevent lengthy interviews, given the high quantities manufactured. Out of 215 producers surveyed at baseline, only two producers never reported sales. Conditional on reporting, the mean producer participated in 9.1 sales tracking calls. The main reason (94 percent) for not participating was unreachability, i.e., the phone was off or not picked up.

Lastly, to collect evidence on rural demand for the medium-sized firewood *Jambar*, we conducted sealed-bid, second-price (“Vickrey”) auctions with 937 randomly selected households in 60 villages.⁵⁸ We first randomly assigned each sample village to a short- or long-survey arm. We then further assigned villages within the long-survey arm to one of two different types of auctions: those featuring only the firewood *Jambar* or those also featuring another improved stove along with the *Jambar* that is currently inexistent in Senegal (see Jeuland et al. 2021).⁵⁹ Within each village, we randomly selected approximately 15 households from village rosters and invited them to participate in auctions. Households in the long-survey arm completed a comprehensive household survey, during which they cast their sealed bids. All bids as well as the results of the auction were revealed during a public event held later in the village. Households in the short-survey arm, in contrast, completed a relatively minimal survey. They

⁵⁷ The reasons for not reporting in a given month were unreachability of vendors (78 percent), e.g., due to turned-off phones; refusal to participate (14 percent); postponement of the interview (six percent), and death (two percent).

⁵⁸ Bidders in a Vickrey (1961) auction cast secret bids. The winner (the auction participant with the highest bid) pays a price equal to the second-highest bid. This characteristic of Vickrey auctions makes them incentive compatible; bidders are incentivized to bid (and thus reveal) their true value for the item being auctioned.

⁵⁹ All villages in the short-survey arm were assigned to auctions featuring only the *Jambar*.

also cast their sealed bids for the *Jambar* during the public village event. In both survey arms, field teams shared information about the benefits associated with the *Jambar* and conducted stove demonstrations before explaining the Vickrey auction rules. In particular, enumerators highlighted how bidding one's maximum WTP for the *Jambar* was the optimal strategy for auction participation as participants risked losing the chance to purchase the device if they underbid and overpaying if they overbid. Once auction results were revealed, the highest bidder was invited to purchase the *Jambar* at a price equal to the second-highest bid.⁶⁰ If this individual refused the purchase offer, field teams moved on to the bidder who cast the next highest bid.⁶¹ The auction ended with the acceptance of a purchase offer, at which point the auction winner made a lump-sum payment for the *Jambar* to field teams.

2.4.3 Summary statistics and balancing

A large set of key vendor and vendor business characteristics are provided in Appendix Table 2C.1. The table outlines, for example, vendors' responses to whether they had ever conducted a list of marketing activities at baseline. The table also shows that the average sample vendor sold only 0.08 firewood *Jambars* and 2.3 charcoal *Jambars* per pre-intervention month, confirming that there is an underdeveloped firewood *Jambar* market at baseline. Monthly sales of other stoves include 0.06 *Sakkanal* stoves and just over one basic metal stove per month.

We conduct a one-way analysis of variance (ANOVA) to test for equality in means at baseline between vendors of the three experimental groups. We look at over 36 vendor and business characteristics. There are only two statistically significant differences, namely preference for immediate pay-off in a hypothetical experiment and whether a vendor refrains from intensifying customer outreach because s/he is not interested in it. In sum, the balancing suggests a successful randomization of our treatments.

2.5 The *Jambar* market

2.5.1 Structure

The *Jambar* producers are metalworking artisans (e.g., whitesmiths) who typically work in small workshops in urban centers. Since 2007, 228 producers were trained by FASEN, of which 215 participated in our survey. At baseline, producers sell considerably more charcoal *Jambars* per typical month on average (44.6), than firewood *Jambars* (10.3), thereby catering to urban

⁶⁰ Each village could have only one winner. In case of multiple bidders casting the winning bid, a winner was selected by drawing lots.

⁶¹ Although auction results were not binding in any legal sense, in practice only six percent of participants declined to follow through with their purchases (see Jeuland et al. 2021 for additional details).

and peri-urban charcoal users. Approximately half of producers produce other ICS, traditional stoves, and doors and windows.⁶² Taken together, 70 percent (24 percent) of producers identified the *Jambar* as one of their most important (medium important) sources of revenues. The producers are all male, on average 37 years old, and 61 percent had no formal education except for Koranic schooling (see Appendix Table 2C.2). Their customers are mostly end-users (catered to by 88 percent of producers), followed by wholesalers and intermediaries (63 percent), and organizations such as non-governmental organizations or women's groups (28 percent). However, wholesalers and intermediaries purchase the largest quantities (57 products per month on average), followed by end-users (24 products) and organizations (12 products). Most producers provide their customers with credits (85 percent). During the 12 months preceding our survey, 73 percent of producers expanded their business to clients in new markets.

Note that, according to FASEN experts, artisans without FASEN training have started producing and marketing a counterfeited version of the *Jambar*, i.e., without a FASEN sticker. At baseline, 62 percent of vendors who already sell the *Jambar* confirm having seen such counterfeits. We cannot quantify the size of the non-FASEN *Jambar* market. Yet, the fact that we can only match 44 percent of the producers that vendors report purchasing from to our FASEN-vendor sample, is suggestive of a substantial counterfeit *Jambar* market.⁶³

Louma kitchenware vendors often operate in multiple *loumas* (three on average at baseline) on most days (21 on average) of a month. Most vendors (66 percent) are male and have no formal education except for Koranic schooling (66 percent) (see Appendix Table 2C.1). They are highly mobile entrepreneurs. Most of them (78 percent) travel to producers or wholesalers to buy stoves, and use public transport (40 percent), rented vehicles (30 percent), their donkey cart or car (15 percent each) for transportation. The vendors' clients purchase in *loumas* (98 percent), pay in cash (98 percent), and are mostly individual women (97 percent) from close-by villages (64 percent). Interestingly, most vendors (93 percent) provide credits or installment payment to their customers. The *Jambar* vendors at baseline roughly agree with producers in that the highest adoption barrier are stove costs (66 percent), missing information about stove benefits (38 percent), and habits and culture (13 percent). However, they add that missing knowledge about the existence of the stove (12 percent) impedes adoption. Over forty percent

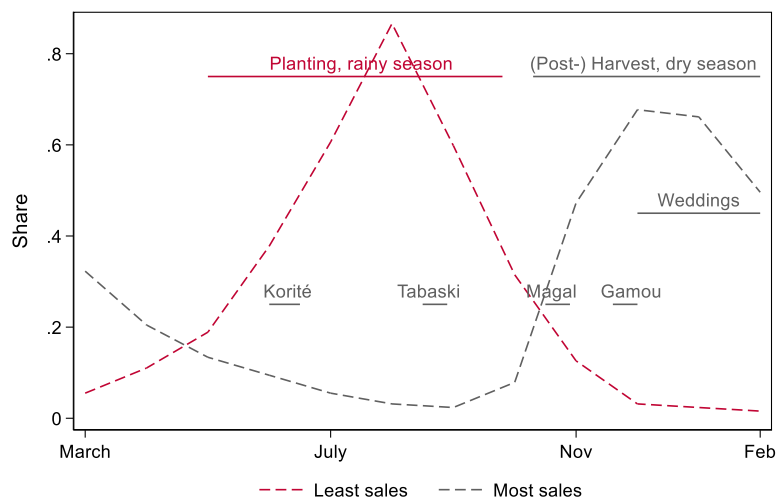
⁶² Other products were general tools, such as hammers and shovels, (31 percent), agricultural tools and machinery (22 percent) and kitchenware (17 percent), such as pots.

⁶³ Yet, the matching may be noisy as vendors may refer to producers by different names or to names of their co-workers they engage with.

of the vendors report a lack of suitable transport as a key barrier inhibiting the growth of their businesses.

Sales volumes in *loumas* are generally characterized by high seasonality. Figure 2.7 plots the share of vendors identifying a month as a low or high sales month at baseline, and roughly temporalizes the vendors' main perceived reasons for these low and high sales. Sales are lowest in the planting and rainy season, when farm incomes are low, infrastructure is inaccessible due to heavy rains, and water-delicate home devices are deteriorating in wet environments (such as some stove types). The end of the year is associated with high sales for several reasons. First, it is the (post-)harvest season with highest incomes. Second, the dry (and colder) season may raise stove demand, as some households use them more regularly to heat water for showering. Third, weddings are celebrated, which is important for stove sales both as the ceremonies are cooking-intensive, and as brides commonly get kitchen utensils as gifts. In the year of our main surveys, two major religious festivities, namely *Gamou* and *Magal*, which bring along massive cooking events for large groups, also took place in the last quarter of the year.

Figure 2.7: Reported seasonality in sales (all products) in loumas and underlying reasons as occurred in 2019



Note: We show the share of vendors identifying a month as a month of “least” or “most” sales. We plot the reasons that increase sales (grey) and decrease sales (red) as reported by most vendors. Religious festivities are plotted as they occurred in 2019 and include: Gamou (celebration of the birth of the prophet Muhammad), Magal (pilgrimage of the Senegalese Mouride Brotherhood), Tabaski (Eid al-Adha/festival of sacrifice), and Korité (Eid al-Fitr/ Ramadan fast breaking).

Rural end-users classically buy non-locally produced goods in *loumas*. *Loumas* take place on fixed weekdays and offer food products, clothes, utensils, sanitary products, and electronics to the local, peri-urban and rural population. Only for specific, hard-to-find products, rural end-users travel to nearby, urban towns.

2.5.2 Profitability of the firewood *Jambar*

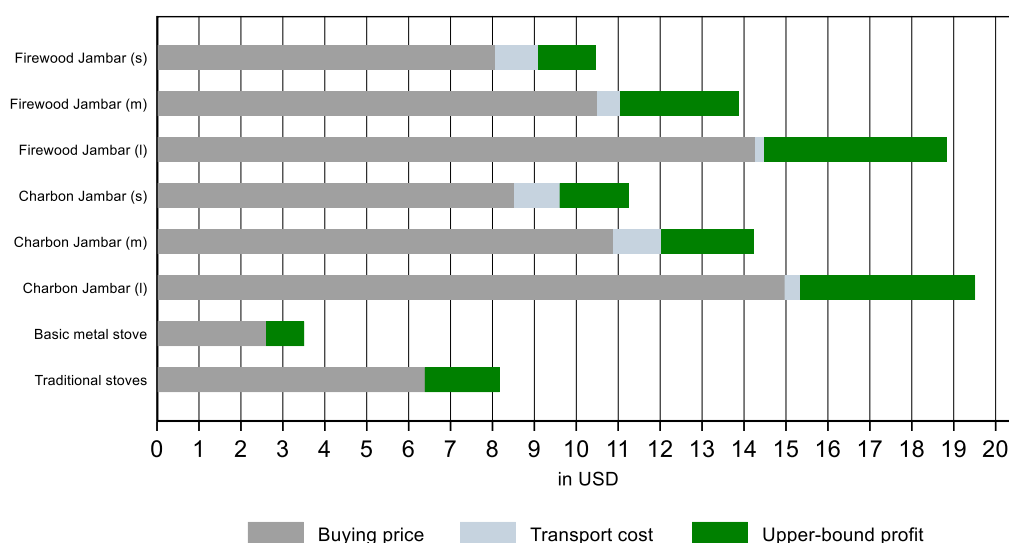
Bensch and Peters (2020) experimentally find an average WTP for the medium-sized firewood *Jambar* of approximately USD 11 in 18 rural Senegalese villages. This WTP covers the prices charged by producers (as reported by vendors at baseline). Building on this prior evidence, we conducted village-level demand surveys during the same season in 60 villages covering large parts of the country, and found a lower WTP for the same, medium-sized firewood *Jambar* amounting to between USD 5–8 (depending on the region). The main difference between our approach and that used by Bensch and Peters (2020) was that we relied on second-price Vickrey auctions (as opposed to the Becker-DeGroot-Marschak method) to elicit WTP. We also experimentally varied (i) the setting where auction participants cast their sealed bids for the *Jambar* (privately at the household, analogous to the door-to-door elicitation carried out by Bensch and Peters 2020, or at a public place in the village during a community event), and (ii) whether the *Jambar* was auctioned alone or along with another improved stove (see Jeuland et al. 2021 for additional details). These differences may partly explain the lower WTP that we observe.

The main assumption underlying our intervention is profitability of firewood *Jambar* sales from the vendors' perspective. This requires presence of unmet, cost-covering demand for the firewood *Jambar* in rural areas. To test the plausibility of this assumption, we next conduct back-of-the-envelope calculations of vendors' profits for the most prominent stove types using costs and prices reported by vendors at baseline. We call for caution in interpreting the point estimates, as sample sizes are small for some stove types, ranging between four and 88 per type, and elicitation of monetary values in an informal business setting is error prone.

The full bars in Figure 2.8 represent the retail prices charged by vendors in *loumas* for different stove types. The colored components show the cost and price structures underlying these retail prices. Vendors at baseline reported the price they pay to producers or wholesalers per stove, the transport costs they pay for bringing a stove to their market or warehouse⁶⁴, and the per-unit retail price they charge for the stove in *louma*. Using these three figures, we calculate the vendors' upper-bound profit.

⁶⁴ 33 percent of vendors get some stoves directly delivered by producers or wholesalers to *loumas* or their storage house and pay a wholesale price that includes transport costs and stove costs. In these cases, transports costs are set to zero.

Figure 2.8: Cost structure of the firewood *Jambar* retail price in loumas, as reported by vendors at baseline



Note: s=small, m=medium, l=large. Profits abstracts from fixed and some variable costs. Transport costs refer to transports from the producer's or wholesaler's location to the vendor's louma or warehouse. For 33 percent of vendors, the transport cost is included in the buying price. This data has substantial missing values, as many stove types are not sold at baseline or as vendors are not willing or able to provide cost calculations. We abstain from imputing these values. The calculations hence rely on a small number of observations ranging between eight and 44 per stove type.

Figure 2.8 shows that vendors set firewood *Jambar* prices such that they earn an upper-bound, per-unit profit ranging from approximately USD 1.5 to 4 depending on stove size and type. Importantly, this profit is the upper-bound profit, as the calculation abstracts from multiple other variable and fixed costs the vendors face in marketing a stove.⁶⁵ This profit level is similar to profits derived from marketing other ICS. Moreover, firewood *Jambar* profits are higher than profits from simpler stoves, possibly due to the risk associated with firewood *Jambar* retail (e.g., *Jambars* are more fragile during often rough transport, retail requires higher up-front investment, and demand patterns are less well known).

The figure also underlines the differences in stove prices end-users face. A medium-sized firewood *Jambar*, for example, costs on average USD 13.6 as compared to USD 5.6 for a basic metal stove and USD 3.4 for a very simple, traditional stove. The simplest, three stone stove is of course free of charge. For low-income households, such difference in prices can be prohibitively high. Appendix Figure 2D.1 shows the cost structure of *Jambar* producers.

Despite lower WTP than previously observed (Bensch and Peters 2020), our demand survey indicates that even in the lower-demand pre-harvest season, approximately 10 percent of

⁶⁵ For the vendor business as a whole, such costs include on average 15 USD weekly for personnel, 5 USD weekly for market taxes and storage, 19 USD for other transport costs, expenses for water, food, electricity and security.

randomly selected households are willing to pay at least the stove price charged by vendors in *loumas* of USD 13.6. This provides support for the main motivation underlying our intervention, namely, that supply-side actors are failing to cater to some pre-existing, potentially profitable, latent demand, thereby inhibiting diffusion of the technology.

2.6 Main empirical approach

Our identification strategy relies on the random assignment of vendors to one of the three experimental groups (control, IM, and IMG). We, moreover, use a generalized difference-in-differences (DiD) approach when baseline data are available and relevant, to improve the precision of our estimates. For our main analysis of vendors' monthly sales, we estimate the following specifications to estimate the impact of receiving any treatment (equation 1a), and of receiving the IM or the IMG treatment (equation 1b):

$$Y_{i,m} = \beta_1(Treatment_i) + \beta_2(Treatment_i \times post_m) + \gamma_m + \epsilon_{i,m} \quad (1a)$$

$$Y_{i,m} = \beta_1(IM_i) + \beta_2(IMG_i) + \beta_3(IM_i \times post_m) + \beta_4(IMG_i \times post_m) + \gamma_m + \epsilon_{i,m} \quad (1b)$$

where $Y_{i,m}$ represents reported monthly stove sales by vendor i in month-year m ; $Treatment_i$ is a binary variable that equals one if vendor i was assigned to *either* of the two supply-side treatment groups; $post_m$ is a binary variable that equals one for all month-years in the post-treatment period; IM_i and IMG_i are binary variables that equal one if vendor i is assigned to the IM or the IMG treatment group, respectively; γ_m represents a month-year fixed effect; and ϵ_i represents a vendor-specific error term. We cluster standard errors at the vendor level. In addition, to control for time-invariant vendor-level differences, as a robustness test we also modify equations (1a) and (1b) to also include vendor fixed-effects (specifications not shown).

For one outcome, namely the use of marketing materials that we provided to vendors as part of the intervention, pre-intervention baseline data are not relevant. In this instance, we estimate the following specification:

$$Y_{i,t+1} = \alpha + \beta_1 Treatment_i + \epsilon_i \quad (2)$$

where $Y_{i,t+1}$ represents an outcome of interest for vendor i at endline ($t + 1$).

Next, we test for temporal heterogeneity by looking at the month-by-month impact of the intervention in an event study set-up. Moreover, we test for heterogeneity across different vendor groups by interacting our intervention with business size, access to banking, marketing activeness and region of the first interview (specifications not shown).

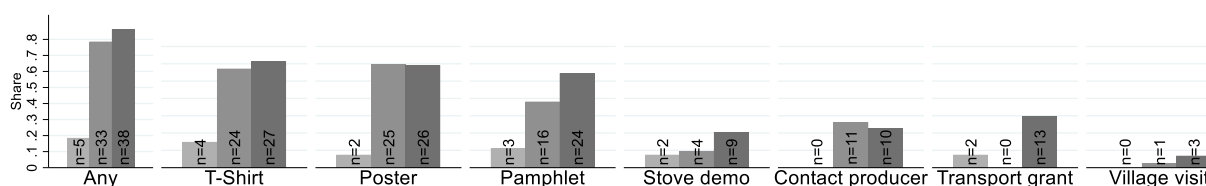
Lastly, we conduct secondary analyses using the DiD and event study set-ups to evaluate the impact of our intervention on upstream sales of firewood *Jambars* by producers, on vendors' long-term sales, on vendors' sales of other stove types, and on joint sales of producers and vendors as a measure of overall market size (not shown here). Remember that these analyses, with the exception of the long-term sales analysis, were pre-specified.

2.7 Results

2.7.1 Treatment uptake

Vendors' use of the various intervention elements is displayed in Figure 2.9. Importantly, the figure only counts uses if they were used directly for marketing the ICS. The first set of bars shows that 86 percent of IMG, 79 percent of IM, and 19 percent of control vendors report using at least one of the elements. Use of the marketing materials distributed by our field team is generally high, ranging from 38 to 60 percent across experimental groups and elements. Use of other components is somewhat lower, and the reasons for not using the elements for stove business purposes vary widely across elements and vendors.⁶⁶

Figure 2.9: Use of treatment elements for stove business, by experimental group



Note: Ordered from left to right: control group (light gray), IM group (gray), IMG group (dark grey). Transport grant use is only counted if the grant was used for transporting stoves. Our definition of use includes the following activities reported by vendors. Use of t-shirt includes wearing to attract clients. Poster use includes informing clients, making marketing passionate, and hanging in stall. Pamphlet use includes informing clients, informing themselves, making marketing passionate, and hanging in stall. Use of stove demonstration includes conducting consumer presentation, conducting cooking demonstration, and showing in shop as marketing. Contact producer includes calling to get price information and calling to make an order. Transport grant includes renting transport/gas to transport stoves to a village and renting transport/gas to bring stoves to a louma. Village visit includes travelling to this or other villages and travelling to find louma customers.

Generally, the figure shows that there were some spillovers to the control group, who did not receive any treatment components from our team. This implies that our effect estimates are lower bound estimates. Spillovers likely results from interactions between vendors, fueled by their high mobility and the generally small number of existent kitchenware vendors.

⁶⁶ Vendors self-reported (in an open question) reasons for not using the elements. For the marketing materials, the main reasons are that the material had been broken or lost or was perceived as uninteresting for marketing by vendors. The demand sheets were difficult to understand (26 percent), lost or broken (22 percent), or vendors did not find the time to use them (20 percent). Producer contacts were not used mostly because vendors already had suppliers (32 percent) or they lost or broke the sheets (23 percent). The demonstration stoves were not used for the stove business, most importantly as they were used privately or given away as a present (57 percent) or there was no demand for them (29 percent). Lastly, transport grants not used for the stove business were mostly used to cover other, non-stove business-related costs than transport (57 percent) or privately (40 percent).

2.7.2 Impacts

We first investigate impacts on self-reported marketing activities.⁶⁷ Specifically, we estimate the effect of the intervention on vendors' propensity to conduct the marketing activities using our treatment elements (equation 2), as well as on their propensity to conduct any marketing activity (both related and unrelated to the intervention).

Table 2.4: Impact of the intervention on vendors' marketing, by experimental group

	(1) Used Jambar T-shirt	(2) Displayed Jambar poster	(3) Conducted village sales visit(s)	(4) Contacted producers	(5) Conducted stove demon.	(6) Used transport grant for sales visit	(7) Any intervention marketing tool	(8) Any marketing tool	(9) Any marketing tool
IM	0.42*** (0.10)	0.52*** (0.092)	0.024 (0.024)	0.26*** (0.069)	0.021 (0.069)	-0.074 (0.051)	0.60*** (0.099)	0.0087 (0.11)	
IMG	0.47*** (0.10)	0.52*** (0.091)	0.068* (0.039)	0.23*** (0.064)	0.13 (0.080)	0.22** (0.086)	0.68*** (0.092)	0.092 (0.12)	
Post								0.057 (0.12)	0.037 (0.12)
IM X Post								0.33** (0.15)	0.39** (0.15)
IMG X Post								0.33** (0.15)	0.37** (0.16)
N	113	113	113	113	113	113	113	240	226
Control/pre-intervention mean ^o	0.15	0.074	0	0	0.074	0.074	0.19	0.43	0.43
Adj. R-sq.	0.13	0.18	0.0047	0.056	0.011	0.14	0.33	0.14	0.19
Vendor FEs	No	No	No	No	No	No	No	No	Yes

*Note: Standard errors (in parentheses) robust to heteroskedasticity; standard errors clustered at the vendor level in columns (8) and (9). Singletons omitted from estimation in column (9). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The marketing elements in (1)-(5) are specific to the intervention and were only provided to treatment vendors. ^oShows control means for columns (1)-(7), and control baseline means for columns (8) and (9).*

Table 2.4 reports the intention-to-treat effects separated by experimental group (see Appendix Table 2E.1 for effect of any treatment). We find that both interventions increased engagement in any marketing activity.⁶⁸ Specifically, as shown in columns (8) and (9), the share of vendors who engage in any marketing activity increased by roughly 30 to 40 percentage points, a statistically significant increase from the full sample's pre-intervention share of 43 percent. In line with our descriptive discussion of treatment uptake (Figure 2.9), this effect is primarily driven by a significant increase in the use of posters (column (2)), marketing T-Shirts (column

⁶⁷ The analysis deviates marginally from the pre-specification, as one question was formulated ambiguously in our questionnaire and as the PAP did not list all treatment elements even though they had been given to vendors before PAP publication (see Appendix Table 2A.1).

⁶⁸ The binary indicator for 'any marketing' includes treatment-related marketing, e.g., deploying *Jambar* posters (Table 2.4 (1)–(5)). In addition, it includes all treatment-unrelated marketing activities, e.g., advertising by SMS/WhatsApp. Vendors reported on these treatment-unrelated marketing activities at both baseline and endline, allowing for a DiD estimation.

(1)), and producer contacts (column (4)) in both treatment groups.⁶⁹ In contrast, only IMG vendors—who received transport grants—conducted village sales visits. This is consistent with vendors in this group having received transport grants to facilitate such visits.

We next turn to impacts on firewood *Jambar* sales. Figure 2.10 presents average monthly firewood *Jambar* sales over time, as reported in our monthly sales tracking. The vertical green line indicates the launch of our intervention in March 2019. Prior to the intervention, reported monthly sales are flat and close to zero. The exception is a peak in sales in February 2018 in the IMG group, which reflects a high-quantity, one-time sale by one IMG vendor. Following the intervention, we observe a sharp increase in reported sales among vendors in the IMG group. Post-intervention sales reported by IM vendors, in contrast, increase slightly. The same is true for control vendors, which, in line with the spillovers in treatment uptake observed above, suggests some level of spillovers.

To empirically assess the impacts of our intervention on vendors’ average monthly sales of the firewood *Jambar*, we estimate a generalized DiD model (equations 1a and 1b). Table 2.5 presents the results. Consistent with the graphical evidence provided in Figure 7, we find that IMG vendors sold approximately 0.9 more firewood *Jambars* per post-intervention month relative to the full sample pre-intervention average of 0.08 sales per month (column (3)). This constitutes a statistically significant change of over 1000 percent.⁷⁰ Reported sales by IM vendors, in contrast, are statistically indistinguishable from those reported by control vendors.

Is the statistically significant increase in reported sales by IMG vendors also economically significant? Accounting for differences in the duration of vendor tracking (i.e., eight months pre-treatment vs. 11 months post-treatment), vendors sold 11.6 firewood *Jambars* per month pre-treatment and 86.5 firewood *Jambars* per-month post-treatment.⁷¹

⁶⁹ Note that, as a potential result from the increased producer contacts, we see that IM and IMG vendors increase the number of stove producers they buy from more between baseline and endline than control vendors (by 0.36 and 0.27 vs. 0.12 producers on average, respectively).

⁷⁰ Among those vendors using the elements, most (94 percent) believe the poster increased the firewood *Jambar* sales, many believe the pamphlets and transport grants did (87 and 84 percent, respectively), two-thirds think the demonstration *Jambars* did, and about half think the demand information and producer contacts increased sales.

⁷¹ Taken together, vendors sold a total of 692 firewood *Jambars* in the post-treatment period compared to 128 in the (longer) pre-treatment period; just under 500 of these additional firewood *Jambars* were sold by IMG vendors.

Figure 2.10: Vendors' average monthly firewood Jambar sales over time, by experimental group

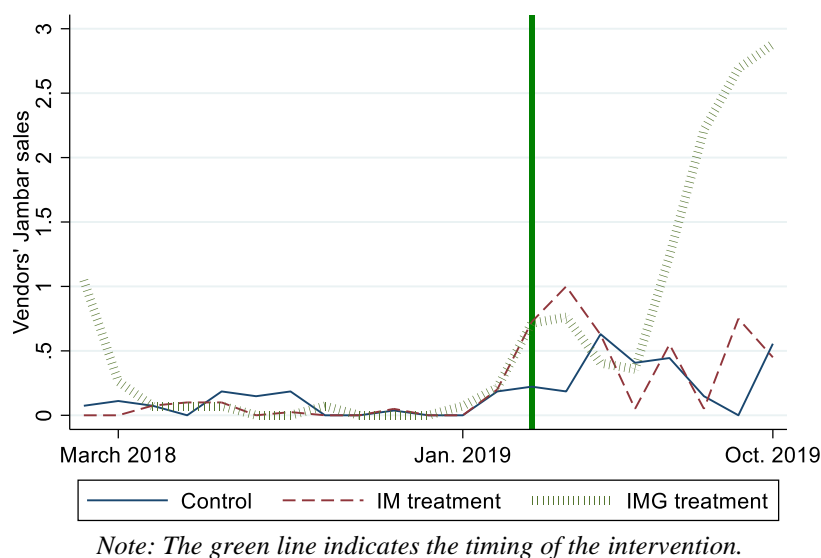


Table 2.5: Impact of the intervention on vendors' monthly firewood Jambar sales

	(1) Firewood Jambars	(2) Firewood Jambars	(3) Firewood Jambars	(4) Firewood Jambars
Any treatment	0.014 (0.059)			
Any treatment X Post	0.51 (0.31)	0.51 (0.31)		
IM			-0.032 (0.035)	
IMG			0.060 (0.10)	
IM X Post			0.15 (0.30)	0.15 (0.30)
IMG X Post			0.88* (0.48)	0.88* (0.48)
N	2667	2667	2667	2667
Pre-intervention mean	0.078	0.078	0.078	0.078
Adjusted R-sq.	0.013	0.12	0.019	0.12
Year-month FEs	Yes	Yes	Yes	Yes
Vendor FEs	No	Yes	No	Yes

Note: Standard errors (in parentheses) clustered at the vendor level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

As we demonstrate in section 2.6.4, these post-intervention sales account for a substantial 33 percent of the total market volume reported by upstream FASEN-trained *Jambar* producers. Yet, the increase is small in absolute terms, considering that we cover a substantial share of louma vendors in a large survey area. It is also small relative to the vendors' sales of other stove types (see section 2.7.7).

2.7.3 Impact heterogeneity

Our analysis showed substantial impact heterogeneity across the IM and IMG treatment groups (Table 5). We next check for heterogeneous effects across four additional dimensions: months, vendor type, individual vendors, and regions. First, Appendix Figure 2F.1 plots treatment effects by month, obtained from estimating the following event study specification:

$$Y_{i,m} = \beta_1(IM_i \times \gamma_m) + \beta_2(IMG_i \times \gamma_m) + \gamma_i + \gamma_m + \epsilon_{i,m} \quad (3)$$

where we interact the IM_i and IMG_i binary variables (representing the two treatment groups) with γ_m (the month–year binary variable) to estimate month–year-specific treatment effects. This figure highlights that there is no difference in pre-intervention sales between control and treatment vendors. Starting with the launch of the intervention in March 2019, however, reported sales by the IMG vendors increase over time. This pattern is consistent both with the self-reported seasonality in vendors’ sales shown in Figure 2.7 and with the rationale that uptake of treatment (usage of marketing materials, networking with producers and/or villages, ordering and marketing of stoves) may take time.

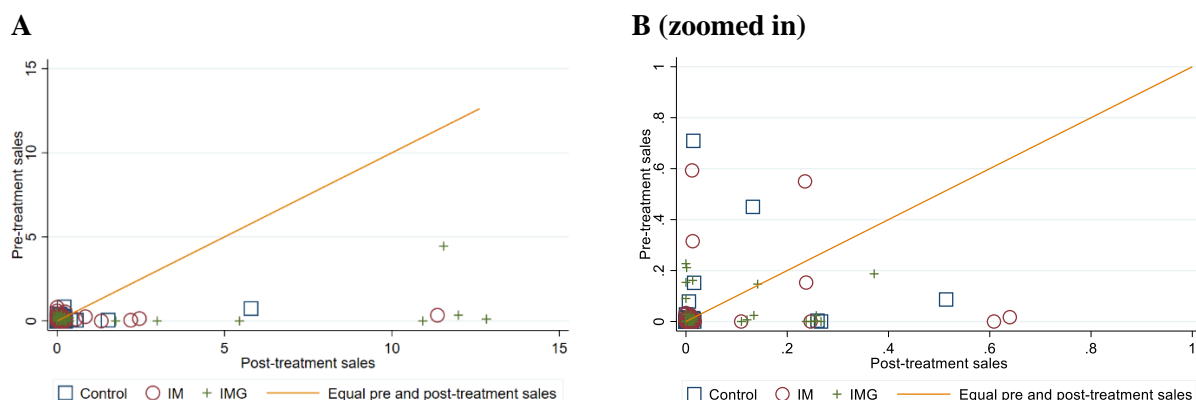
Second, we investigate whether effects on firewood *Jambar* sales and on post-intervention marketing differ across different vendor baseline characteristics as pre-specified in our PAP: (i) large or small business⁷², (ii) access to banking services, and (iii) engagement in marketing activities. We find no evidence for differential effects on marketing activities nor sales across the groups of vendors (results available upon request).

Third, we assess heterogeneity in response to our intervention across individual vendors. Note that this descriptive analysis was not pre-specified. Figure 2.11 plots each vendor’s average monthly firewood *Jambar* sales before the intervention against sales after the intervention, i.e., vendors on the 45° line kept sales constant. Panel A displays all vendors, and Panel B zooms in on vendors with lower sales numbers, ranging between zero and one monthly sales.

The figure conveys, most importantly, that the increase in post-treatment sales is driven by a small number of “super-sellers”. There are five vendors who sell more than five *Jambars* per month on average in the IMG group, and one each in the IM and control group (Panel A). Moreover, it shows that there are only a few vendors, mostly from the control and IM groups, who reduce their firewood *Jambar* sales slightly (Panel B).

⁷² Based on median monthly revenue as well as the median number of products sold.

Figure 2.11: Vendors' average monthly firewood Jambar sales, pre- and post-treatment by experimental group



The fact that a few vendors translate our treatments into much larger increases in sales than others is in line with Grimm et al. (2012), who segment informal, urban entrepreneurs from seven West-African countries into top-performers, survivalists and “constrained gazelles”: entrepreneurs with low capital and high locked potential. In their analysis, the main predictors of top performance are schooling, speaking French, higher age, and being male. It is also roughly in line with the microfinance literature, which finds more positive impacts of microcredit on business profits if the businesses were established already before access to microcredit (see Meager 2019), if microentrepreneurs have higher entrepreneurial skills or household wealth (De Mel et al. 2008), or if owners are male (Fiala 2018).⁷³

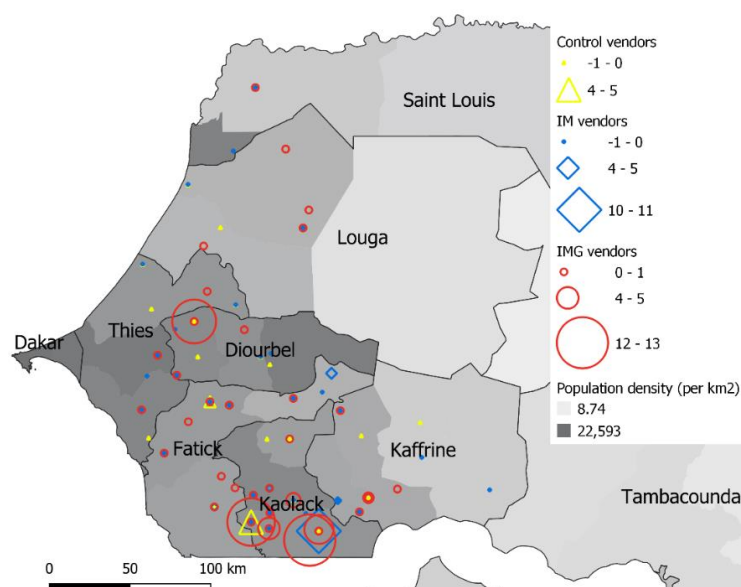
Acknowledging the very small sample size of “super-sellers”, we see that a higher share of “super-sellers” at baseline names “access to credit” as their first barrier to business growth (57 vs. 22 percent), names people from small villages as principal clients (100 vs. 62 percent) and did not buy from producers directly already before our intervention (80 vs. 43 percent).

Fourth, we look further into regional heterogeneities. Again, this analysis was not pre-specified but became indispensable when looking at the data. Figure 2.12 shows the absolute increases from pre- to post-treatment months of all vendors spatially and by experimental group. We see that six of the seven “super-sellers” were first surveyed in Kaolack, suggesting an interaction effect between treatment and region. This impression also holds qualitatively when considering all *loumas* the vendors operate in or looking at relative increases (not shown).

⁷³ Given the very small sample, we cannot empirically test whether these characteristics are associated with sales growth in our setting. Descriptively and taken with much caution, we see that more “super-sellers” than “non-super-sellers” at baseline have below median revenues (42 vs. 53 percent), are women (43 vs. 33 percent), have no formal education (86 vs. 65 percent), and sell traditional stoves (57 percent vs. 28) and other improved stoves (43 vs. 27 percent).

To better understand differences between regions, we show a set of regional characteristics in Appendix Figure 2F.1. Empirically, the interaction of Kaolack and the treatment is large but not significant, likely because of the very small sub-sample sizes (results available upon request).⁷⁴

Figure 2.12: Average absolute change in firewood Jambar sales between pre- and post-treatment months, by vendor and market location



Source: Own presentation. Population data from the Minnesota Population Center (MPC 2020) based on 2013 census data by the National Agency of Statistics and Demography (ANSD). Areas calculated using QGIS3. Note: The figure displays each vendor in the louma s/he was first interviewed in. It sizes vendors by the absolute growth in their average monthly sales between pre-treatment and post-treatment months.

2.7.4 Robustness

Our impact results are robust to various modifications of our specification. First, they are robust to the inclusion of vendor fixed-effects to control for unobserved vendor-level heterogeneity (columns (2) and (4) in Table 2.5). Second, they are robust to the sequential inclusion of control variables into the regression (Appendix Figure 2E.1). Third, we find significant effects also when looking at an alternative measure of our main outcome, namely vendors’ reported sales in a *typical* month in the endline survey (instead of vendors’ monthly reported sales) (Appendix Table 2E.2). Fourth, we test our results for robustness to outliers using three distinct procedures (see Appendix Table 2E.3). While the test shows that our results are sensitive to winsorizing or trimming the highest sales, this is in line with the finding that only few “super-sellers” substantially raise sales as a response to our treatment (see section 2.7.3).

⁷⁴ Note that we do find some evidence that the treatment is significantly *less* effective in two regions, namely Fatick and Louga (results available upon request).

Lastly, we assess the robustness of our results to two distinct forms of attrition in reporting: non-response at endline, and non-response during monthly sales reporting.⁷⁵ Our analyses can suffer from two forms of attrition, namely in the in-person endline surveys asking for sales in a typical month and marketing activities, and in the monthly sales reporting. First, at endline, attrition is balanced across groups, but relatively high at 11 percent (see Table 2.3). In Appendix Figure 2E.2 we show that our findings regarding the use of marketing materials are broadly robust to all possible assumptions about the values that the 14 attrited vendors' marketing-related outcomes can take.⁷⁶ Similarly, in Appendix Figure 2E.3 we show that our findings regarding IMG vendors' sales of the firewood *Jambar* in a typical month (Appendix Table 2E.2) remain significantly higher than other vendors' sales using a simulation-based approach to assume sales levels for attrited or non-responsive vendors. Second, there is balanced but substantial variation in monthly sales reporting. For example, the median number of reported months is 10-11 (see Table 2.3). We foresaw attrition in interim months given that vendors are highly mobile and occupied entrepreneurs. We therefore asked vendors to report sales since their last reporting, and thereby retrieved sales that interim attritors had not yet reported. Interim attrition in monthly reporting is therefore unlikely to bias effects between experimental groups, but less reporting may lead to noisier sales estimates. A third instance of attrition, namely attrition in long-term sales reporting, is discussed in section 2.7.6.

A remaining threat to the internal validity of our estimates is the possibility of spillovers from treated to control vendors. Spillovers, as shown above, are plausible given that interaction between vendors seems high in these informal economies: vendors are mobile, operating on average in three different *loumas*, and 36 percent of the surveyed vendors report cooperating with other stove vendors.

The slight post-intervention increase in sales of firewood *Jambars* among control vendors could arise from

- (i) direct treatment contamination in the control group, for example because vendors shared treatment information or materials (Figure 2.9),
- (ii) indirect information spillovers, because control vendors observe and imitate treatment vendors' firewood *Jambar* marketing or sales (Figure 2.9),

⁷⁵ Note that we partly deviate from our pre-specified analyses (see Appendix Table 2A.1 for details).

⁷⁶ The only exception is that the conduct of sales visits is no longer statistically significant for the IMG group, which is not surprising given the only marginally significant effect observed in our main analysis.

- (iii) demand spillovers, as customers reach out to control vendors after having learned about the firewood *Jambar* from treatment vendors,
- (iv) general equilibrium effects (GEE) as demand for the firewood *Jambar* multiplies through its increased visibility in *loumas* and villages and increased experimentation with the stove among the local population.

Both, direct sharing of elements (i) and learning by observation (ii) are likely⁷⁷, whereas demand spillovers and GEE effects are less plausible in our setting due to the low number of additional firewood *Jambar* sales in absolute terms. All possibilities would imply we underestimate the treatment effects.

2.7.5 Impacts on upstream producers' sales

We now assess whether the increased firewood *Jambar* sales in *loumas* vertically impacted firewood *Jambar* volumes sold by upstream producers, or volumes sold jointly by producers and vendors. This analysis provides evidence on the magnitude and economic significance of our intervention's impact.

Appendix Table 2G.1 shows that we find no evidence to suggest that the start of the vendor-level intervention increased sales of upstream producers, not separately for producers' sales of the three different sizes of the firewood *Jambar*, nor for the sum thereof. Looking at joint sales by vendors and producers – as a measure of full market volume⁷⁸ – we once again find no evidence to suggest a distinguishable growth in the overall size of this market (see Table 2G.1 column (5)).

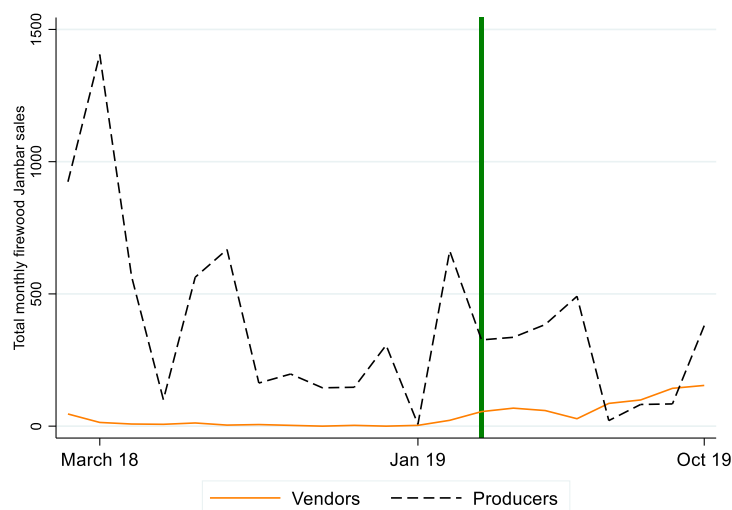
Our analysis has shown that the impact of our intervention is significant for IMG vendors, and most substantial for some “super-sellers”. To shed light on the economic significance of these effects, Figure 2.13 plots the total firewood *Jambar* sales of surveyed vendors and producers over time. It highlights that there are large over-time fluctuations in producers' sales and a slight downward trend. Moreover, the absence of a treatment effect on upstream producers' sales is plausible, firstly, as a large treatment effect on producers' sales would be required to

⁷⁷ Our data allow us to descriptively assess the plausibility of (i) and (ii). Regarding (i) direct contamination, some control vendors report having heard about or seen our demand information sheets (15 percent), producer contacts (12 percent), and transport grants (23 percent). All these elements can be kept private if desired and must hence have been shared intentionally by treatment vendors. Our data also provide some more evidence for (ii) spillovers on control vendors by observation of treatment vendors. Control vendors report having seen or heard about firewood *Jambar* T-shirts (60 percent), firewood *Jambar* posters (42 percent), the “Do's and Don'ts” pamphlet (31 percent), and the demonstration firewood *Jambars* (38 percent). These treatment elements can hardly be kept private (if used) in a market setting.

⁷⁸ Note that firewood *Jambars* sold by surveyed vendors from surveyed producers are counted twice in this analysis, making it an imperfect measure of firewood market volume. We therefore do not discuss this further.

compensate for the downward trend in their sales. Second, as vendors' sales in the eight post-intervention months only account for 33 percent of the market volume of FASEN-trained producers.⁷⁹ However, this is an upper-bound value, as artisans, who have not been trained by FASEN, have started to produce counterfeited *Jambar* stoves (see discussion section 2.5.1).

Figure 2.13: Firewood *Jambar* market volume, by market actor



Note: The green line indicates the timing of the intervention.

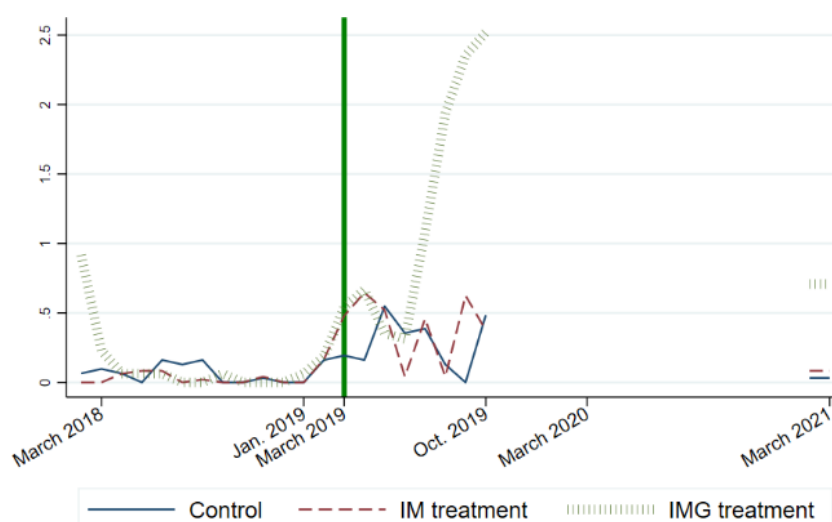
2.7.6 Long-term impacts

If the treatment set off a sustained cycle of increased firewood *Jambar* supply and potentially demand, vendors' sales would increase further in the long-term. We test whether the increases in vendors' firewood *Jambar* sales are sustainable by means of an additional sales tracking survey in March 2021, roughly 1.5 years after the last sales tracking survey (October 2019) and two years after the intervention (March 2019). Note that this analysis was not pre-specified as it only became possible through additional funding at a later stage. In line with sales tracking in previous months, we asked vendors for each stove sale during the four weeks preceding our call. We surveyed 93 vendors, i.e., 73 percent of vendors of our initial sample. We did not reach 27 vendors as their phones were not functional, five declined to participate, and two had passed away. Response is imbalanced across groups and increases with the extent of the treatment: 61 percent of control, 69 percent of IM, and 85 percent of IMG vendors participated in our long-term survey, a difference that is significant at the five percent level. Our analysis below therefore addresses non-balanced attrition.

⁷⁹ Specifically, vendors sold 692 stoves as compared to 2,104 stoves sold by producers during the eight post-intervention months.

Between March 27th and June 30th, 2020, the Senegalese government proclaimed a state of health emergency and took measures to curb the spread of COVID-19, which directly targeted rural markets and hence plausibly negatively affected (sales of) *louma* vendors.⁸⁰ Measures included, among others, a reduction of working days in fixed markets and a ban on traveling between departments, on weekly *loumas*, and on public gatherings and festivities. When asked in March 2021, 73 percent of vendors indeed report a negative impact of the pandemic (-related measures) on stove sales and sales in general, and another 20 percent report not to know the direction of the effect. In an open comment, five vendors even report having left the stove business.

Figure 2.14: Vendors’ average monthly firewood Jambar sales in the long run, by experimental group



Descriptively, Figure 2.14 shows that two years after the intervention, sales of IMG vendors are higher than those of IM and control vendors.⁸¹ Yet, sales dropped in magnitude relative to the previous sales tracking, which could be due to (i) COVID-19, (ii) a declining treatment effect over time, and/or (iii) seasonality (average sales are of similar magnitude as in the same post-treatment month two years earlier).

⁸⁰ Weaker measures (night curfews) were re-introduced between December 2020 and March 2021 in the regions Dakar and Thiès.

⁸¹ Following up specifically on the seven “super-sellers”, i.e., vendors with previously more than five firewood *Jambar* sales per month on average, we see that one (IMG) could not be reached, and one (IMG) remains a “super-seller” with 10 monthly sales. Yet, five “super-sellers” did not sell as many firewood *Jambars* as previously of which four blame COVID-19 directly. However, for this one follow-up month (March 2019), two new “super-sellers” emerge with six and 10 sales.

Table 2.6: Impact of the intervention on monthly firewood Jambar sales in the long run, by experimental group

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Firewood Jambars	Firewood Jambars	Firewood Jambars	Firewood Jambars	Firewood Jambars	Firewood Jambars	Firewood Jambars	Firewood Jambars
Any treatment	0.014 (0.059)				0.014 (0.059)			
Any treatment X Post	0.44* (0.25)	0.44* (0.25)			0.47* (0.26)	0.47* (0.26)		
IM			-0.032 (0.035)				-0.032 (0.035)	
IMG			0.060 (0.10)				0.060 (0.10)	
IM X Post			0.13 (0.24)	0.13 (0.24)			0.19 (0.29)	0.19 (0.29)
IMG X Post			0.76** (0.38)	0.76** (0.38)			0.76* (0.38)	0.76* (0.38)
N	2921	2921	2921	2921	2921	2921	2921	2921
Pre- intervention mean	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.078
Adjusted R- sq.	0.013	0.11	0.019	0.11	0.013	0.12	0.018	0.12
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Vendor FEs	No	Yes	No	Yes	No	Yes	No	Yes
Attrition adjustment	Zero	Zero	Zero	Zero	Maximum	Maximum	Maximum	Maximum

*Note: Standard errors (in parentheses) clustered at the vendor level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Columns (1)-(4) set sales of attriting vendors to zero; columns (5)-(8) sets them to the vendors' all-time maximum monthly sales.*

Table 6 presents treatment effect estimates using our main DiD specification, and two alternative approaches to handling non-balanced attrition. First, the 2021 sales of attriting vendors are set to zero (columns (1)-(4)) and second, they are replaced by the attriting vendors' all-time maximum monthly sales of all months (columns (5)-(8)). The latter approach is very conservative, as it maximizes sales of more control vendors than treatment vendors, given that more control vendors attrited. Table 6 shows that the IMG treatment effect remains also in the long-run, two years after the intervention despite COVID-19 measures, whereas the IM treatment remains insignificant. The effect size is only marginally smaller than the shorter-term effect sizes (Table 5), and significance drops to the 10 percent level when adjusting conservatively for non-balanced attrition.

2.7.7 Impacts on vendors' louma-level sales of other stove types

Our treatment may have affected sales of other stove types negatively or positively. Yes, due to the small absolute increase in firewood *Jambar* sales in response to our treatment and the still much higher sales numbers of traditional stoves, we cannot expect a discernible crowding-out effect on traditional stoves (as hypothesized in our conceptual rationale, see Figure 1.2). We do also not expect the intervention to crowd out the sales of other ICS as only few vendors were offering other ICS in the first place. Yet, our treatment may have positively affected sales of other stove types as there was some transferability of treatments to other stove types, constituting cross-product externalities. While treatment vendors could use some treatment elements exclusively to increase firewood *Jambar* sales (e.g., access to demonstration stoves and WTP information), other elements may have helped boosting charcoal *Jambar* sales due to the stoves' similarity (e.g., marketing materials), or even *Sakkanal* sales (e.g., advertising the benefits of ICS in general). The producer contacts, the stronger business focus on stoves, the sensitization for new marketing approaches and the grant labelled for stove transport may have also been used to promote sales of traditional stoves or even other wares.

We test whether the increased sales of the firewood *Jambar* horizontally affected vendors' sales of other stove types, both in our main tracking period and in the long-term. We descriptively show that *Sakkanal* sales trend upwards among IMG vendors and remain very high, and higher than firewood *Jambar* sales, even in the long-run and in the low-sales, planting season (Appendix Figure 2H.1). The increase is positive and significant in the IMG group (see Appendix Figure 2H.1).⁸² The IM and IMG treatments do not significantly affect sales of traditional stoves or charcoal *Jambar*. Sales of traditional stoves are higher among IMG vendors but fluctuate strongly both before and after the intervention across groups. Charcoal *Jambar* sales trend upwards already before the intervention and across experimental groups, plausibly reflecting increased sales to better-off and/or more urban customers.

We derive two important lessons from these results. First, our intervention has generated co-benefits via increased sales of another, welfare-improving ICS variant. This is highly plausible as sales of the two ICS may be co-integrated within the vendors' business models, as they have similar producer, customer, transport, and pricing structures. This also underlines the advantage of relying on pre-existing market mechanisms for technology diffusion: demand and supply can

⁸² Despite a very conservative correction for non-balanced attrition in the 2021 long-term survey and some spillovers to the control group, the effect is significant at the five percent level and in magnitude even slightly larger than the impact on firewood *Jambar* sales.

flexibly react to preferences and, as in this case, use reduced IMG barriers to respond to latent demand as it occurs.

Second, this finding points to an important risk inherent to relying on pre-existing market mechanisms. Private sector actors may convert reduced barriers also into sales of technologies that are not necessarily welfare improving from a societal or environmental perspective. While this may be profitable and desirable from a vendor perspective, it defeats the purpose of such intervention. We here do not observe such effects (on traditional stove sales) but see some descriptive indication for it in the long-term survey (Figure 2F.1 Panel D). We derive from this that similar policy engagement with the private sector must manage incentives and side effects very thoroughly.

2.7.8 Diffusion cost

The value of our intervention for policy action depends – next to its relevance – on its cost-effectiveness. As a first step towards assessing cost-effectiveness, we provide back-of-the-envelope calculations of the per *Jambar* diffusion cost. The total cost of delivering our IMG intervention is roughly USD 319 per IM vendor and USD 350 per IMG vendor. The cost excludes monthly sales tracking cost, which was done for evaluation purposes only.⁸³ The cost is calculated for 96 vendors surveyed in 60 *loumas* and will vary considerably at different scales or geographical coverage. Figure 2.15 spreads the total intervention cost over the additional firewood *Jambar* sales triggered by our intervention. Specifically, the solid lines show the cost per stove disseminated over time for the IM and IMG group. We calculate these additional sales conservatively.⁸⁴

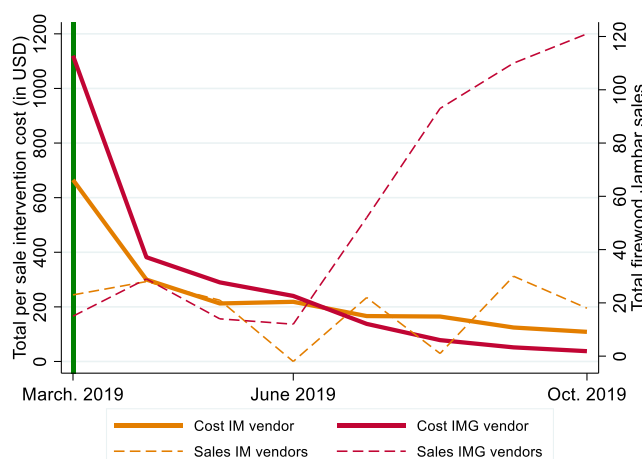
In the eight months from the intervention (March 2019) to the end of the main monitoring (October 2019), the total intervention cost per firewood *Jambar* diffused decreases from USD 665 to 109 for IM vendors and from USD 1,120 to 38 for IMG vendors (Figure 2.15). While the dissemination cost via the IM intervention seems out of proportion given the much lower price of the stove itself, the cost of dissemination via IMG may prove competitive with

⁸³ This calculation hence implicitly assumes that the regular sales tracking did not impact vendors' sales. The cost includes, among others, costs for materials, sample stoves, and transport grants, a permanent junior staff, field personnel and logistical costs to identify vendors and deliver the intervention, and implementation of auctions in villages.

⁸⁴ To quantify additional firewood *Jambars* sold, we calculate the before-after difference in *Jambars* sold, i.e., we take the firewood *Jambar* sales of each experimental group in each post-intervention month and subtract the sales from the same month and group in the previous (pre-intervention) year. We prefer this conservative approach over the alternative approach that would take the difference in sales between treatment and control groups in the same month (leading to somewhat higher *Jambar* sales and thereby a lower diffusion cost due to spillovers on control vendors).

alternative dissemination policies. Note that a large share of the cost is associated with the village-level WTP survey, a treatment element that may or may not be necessary for the observed impacts to occur. Also note that this calculation does not yet include co-benefits generated via additional *Sakkanal* ICS sales.

Figure 2.15: Intervention cost per additional firewood Jambar sale, by experimental group



Note: The left axis and solid lines display developments of the total intervention cost per firewood Jambar sale; the right axis and dashed lines display developments of sales. The figure spreads the intervention cost over the additional firewood Jambars sold over time.

The final cost of stove diffusion will decline further with continued sales over time. Our discussion of long-term impacts (section 2.7.6) tentatively suggests that the cost per diffused firewood *Jambar* kept decreasing roughly at a similar pace as in the first year after the intervention despite negative market impacts of the COVID-19 pandemic and policies. Assuming the same average changes in monthly sales as observed over the first eight months of monitoring, the IMG diffusion cost goes down, for example to roughly USD 15 after another 12 months. This diffusion cost needs to be compared to the cost of alternative distribution mechanisms, such as establishing completely new sales channels, investing in demand-side sensitization, or bringing technologies to rural areas by means of NGOs.

Next to assessing per-stove diffusion cost, one needs to run full-fledged cost-benefit analyses to assess whether the cost per diffused stove is a worthy investment from a welfare perspective. A holistic cost-benefit analysis is out of the scope of this chapter. It would need to assess impacts of diffused stoves among others on (i) vendors' overall sales and profits, (ii) spillovers on other vendors' and producers' sales and profits, and (iii) cost-benefits of firewood *Jambar* adoption for end-users and the local environment.

2.8 Conclusion

Our intervention has provided some of the first empirical evidence on the potential of supply-side interventions to boost diffusion of welfare-improving technologies in rural settings. Specifically, it has tested a policy tool that relies on pre-existing markets and “late-mile”, private sector actors to improve accessibility of the firewood *Jambar* ICS in remote Senegalese villages and thereby to meet latent demand of rural customers. The firewood *Jambar* is promoted by the Senegalese government to reduce deforestation and improve the wellbeing of firewood-reliant households. However, diffusion has been low in rural areas, where firewood-reliance is highest.

In the last decade, the private and public sectors have pioneered business models and delivery channels to boost ICS diffusion across the Global South, for example by establishing new delivery channels or partnering up with grassroots sales agents or village-based organizations. While research has pointed to the importance of fostering robust supply chains as a pathway to widespread uptake of ICS (e.g., Pattanayak et al. 2019, Bensch and Peters 2020), it has overwhelmingly focused on demand-side drivers of adoption, such as rebates/grants and health information dissemination (e.g., Mobarak et al. 2012, Levine et al. 2018, Beltramo et al. 2015).

Our RCT has shown that a low-cost treatment combining informational, marketing, and financial support can incentivize intermediary vendors in weekly markets to successfully diffuse a demanded technology. We have shown that this effect did not only increase for the eight months succeeding the intervention, but also endured two years after the intervention despite market disruptions from COVID-19 policies. Yet importantly, the treatment is only effective if it includes financial support, and exclusively incentivized some “super-sellers”, but not others, to increase diffusion of the technology. While the treatment effects were large relative to vendors’ low baseline levels of firewood *Jambar* stove sales, they are small in absolute terms and therefore did not have a discernible effect on *Jambar* sales by upstream stove producers. Supply-side interventions alone, it therefore seems, will not be sufficient to achieve substantial technology diffusion. Lastly, we have shown that our intervention also positively impacted sales of other ICS types, which we have interpreted as co-benefits of our treatment, and as a potential of the policy tool in general. Yet, this finding also calls for managing incentives thoroughly when engaging in similar cooperation with private sector actors to prevent unintentional side effects.

Our study faces two main threats to internal validity. First, we cannot definitively rule out that vendors in the treatment group overstate their self-reported sales or their marketing activities in

response to the intervention. Yet, vendors would have to overstate sales of some stoves (firewood *Jambar*, *Sakkanal*), but not of others (charcoal *Jambar*, traditional stoves), a behavior that is rather implausible. Second, we recognize that in tracking vendors' stove sales monthly, our survey activities have the potential to elevate the stove component of their businesses. Our estimated coefficients would then no longer represent the average treatment effect of the intervention alone, but rather the joint effect of the intervention in the presence of monthly vendor tracking. Yet, given that we also tracked sales of control vendors, this “mental bookkeeping” raises inferential and hence internal validity concerns only if monthly vendor tracking interacts non-linearly with the core elements of our intervention. Third, given that sample vendors travel to multiple *loumas* and interact routinely with other vendors, our ability (and wish) to prevent spillovers is limited. As a response, we have evaluated the extent to which spillovers to untreated vendors may have occurred by descriptively studying how they used, responded to, or were aware of different elements of our intervention at endline. Additionally, we interpret our estimated coefficients as lower-bound impacts of the intervention.

Our study also faces three threats to external validity. First, our intervention targets one part of the market and is hence generally prone to GEE effects that kick in at scale. For example, treated vendors might benefit from a first-mover advantage and acquire the most profitable rural customers, which makes selling stoves in the future more difficult for other vendors. Or, the first stoves sold in villages might pave the way for higher future sales as early adopters spread the word about stove-use benefits among their networks. Second, it is unclear whether a scaled version of the programme would be as effectively implemented as done by our well-trained field team. For example, if at scale sales tracking proves infeasible, a supply-side intervention modelled after our own may prove less efficacious (see discussion of internal validity above), posing a risk to external validity. Third, as in any study, our insights are drawn from a specific context. For example, we build on prior FASEN engagement and engage in a West African context that has a Sahelian climate, in which firewood is scarce and the reliance on solid fuels and traditional stoves is high. The extent to which these insights generalize to other settings, seasons or technologies remains an open question.

Our study is a proof-of-concept that interventions targeting intermediary vendors in hitherto non-existent ICS markets can be effective. It demonstrates that information is imperfect, and that intermediaries hence cannot be expected to access information about potential downstream demand and upstream supply. Yet, it also shows that while this information is important, it is not enough to incentivize vendors to reach out to underserved customers, financial (transport)

barriers need to be overcome as well. While the additional sales we observed are noteworthy, they are insufficient for the rural stove market to take off substantially. Given the low profile of our intervention and the size of the potential rural market, this is not unexpected.

Our findings indicate that the instrument we have tested can be scaled to improve the availability of firewood *Jambar* stoves in rural areas. Seemingly unrelated policies that facilitate the approaches that we adopted (e.g., improved transport links between urban, peri-urban and rural areas) could also enable existing private-sector operators to begin making inroads into remote villages. While we have demonstrated the importance of the supply side of cookstove markets, it should not preclude the continued use of demand-side instruments to facilitate widespread adoption and uptake of these technologies. Financing schemes and grants, for instance, remain crucial tools to increase affordability. Others (such as vouchers) may simultaneously increase the profitability of rural supply chains. Indeed, it remains unclear whether the WTP for the locally produced firewood *Jambar* stove in rural Senegal is high enough to make it attractive for vendors to systematically reach out to these customers. But our study has shown that some vendors are able and willing to try.

Our contribution to the academic literature is an important piece of evidence to understand the difficulty of fostering and expanding rural markets, in which risks are high and information is costly. This chapter built on scant prior work on the importance of intermediaries and demonstrated its applicability to the domain of ICS and household energy.

References Chapter 2

- Aggarwal, Shilpa, Brian Giera, Dahyeon Jeong, Jonathan Robinson, and Alan Spearot.** 2018. Market Access, Trade Costs, and Technology Adoption: Evidence from Northern Tanzania. National Bureau of Economic Research. Working Paper Series, Working Paper 25253.
- Aker, Jenny C.** 2010. Information from markets near and far: Mobile phones and agricultural markets in Niger. *American Economic Journal: Applied Economics* 2(3): 46-59.
- Allen, Treb.** 2014. Information frictions in trade. *Econometrica* 82(6): 2041-2083.
- Anenberg, Susan C., Kalpana Balakrishnan, James Jetter, Omar Masera, Sumi Mehta, Jacob Moss, and Veerabhadran Ramanathan.** 2013. Cleaner cooking solutions to achieve health, climate, and economic cobenefits. *Environmental Science and Technology* 47(9): 3944-3952.
- ANSD (Agence National de la Statistique et de la Démographie).** 2014. Recensement général de la population et de l'habitat, de l'agriculture et de l'élevage (RGPHAE) 2013: rapport provisoire.
- Arimoto, Yutaka, Hisaki Kono, Tsilavo Ralandison, Takeshi Sakurai, and Kazushi Takahashi.** 2019. Price and Nonprice Information Frictions in Regional Arbitrage: The Case of Rice Traders in Antananarivo, Madagascar. *Economic Development and Cultural Change* 67(2): 273-313.
- Bailis Robert, Rudi Drigo, Adrian Ghilardi, and Omar Masera.** 2015. The carbon footprint of traditional woodfuels. *Nature Climate Change* 5: 266-72.
- Beltramo, Theresa, Garrick Blalock, David I. Levine, and Andrew M. Simons.** 2015. The effect of marketing messages and payment over time on willingness to pay for fuel-efficient cookstoves. *Journal of Economic Behavior and Organization* 118: 333-345.
- Bensch, Gunther, and Jörg Peters.** 2015. The intensive margin of technology adoption—Experimental evidence on improved cooking stoves in rural Senegal. *Journal of health economics* 42: 44-63.
- Bensch, Gunther, and Jörg Peters.** 2020. One-off grants and long-run adoption – Experimental evidence on improved cooking stoves in Senegal. *American Journal of Agricultural Economics* 102(1): 72-90.
- Bergquist, Lauren Falcao, and Michael Dinerstein.** 2020. Competition and Entry in Agricultural Markets: Experimental Evidence from Kenya. *American Economic Review* 110(12): 3705-47.
- Brooks, Wyatt, and Kevin Donovan.** 2020. Eliminating uncertainty in market access: The impact of new bridges in rural Nicaragua, *Econometrica* 88(5): 1965-1997.
- Casaburi, Lorenzo, and Tristan Reed.** 2020. Interlinked Transactions and Competition: Experimental Evidence from Cocoa Markets. Unpublished manuscript.
- Caselli, Francesco, and Wilbur John Coleman.** 2001. Cross-Country Technology Diffusion: The Case of Computers. *American Economic Review* 91(2): 328-335.
- Comin, Diego, and Bart Hobijn.** 2010. An exploration of technology diffusion. *American Economic Review* 100(5): 2031-59.
- Cunningham, Wendy V., and William F. Maloney.** 2001. Heterogeneity among Mexico's microenterprises: An application of factor and cluster analysis. *Economic Development and Cultural Change* 50(1): 131-156.
- Datta, Saugato.** 2012. The impact of improved highways on Indian firms. *Journal of Development Economics* 99(1): 46-57.
- De Mel, Suresh, David McKenzie, Christopher Woodruff.** 2008. Returns to capital in microenterprises: evidence from a field experiment. *The quarterly journal of Economics* 123(4): 1329-1372.

- De Mel, Suresh, David McKenzie, Christopher Woodruff.** 2011. Getting credit to high return microentrepreneurs: The results of an information intervention. *The World Bank Economic Review* 25(3): 456-485.
- De Mel, Suresh, David McKenzie, Christopher Woodruff.** 2012. One-time transfers of cash or capital have long-lasting effects on microenterprises in Sri Lanka. *Science* 335(6071): 962-966.
- Fafchamps, Marcel, Eleni Gabre-Madhin, and Bart Minten.** 2005. Increasing returns and market efficiency in agricultural trade. *Journal of Development Economics* 78(2): 406-442.
- Fafchamps, Marcel, and Bart Minten.** 2012. Impact of SMS-based agricultural information on Indian farmers. *The World Bank Economic Review* 26(3): 383-414.
- Fafchamps, Marcel, David McKenzie, Simon Quinn, and Christopher Woodruff.** 2014. Microenterprise growth and the flypaper effect: Evidence from a randomized experiment in Ghana. *Journal of Development Economics* 106(C): 211-226.
- Fiala, Nathan.** 2018. Returns to microcredit, cash grants and training for male and female microentrepreneurs in Uganda. *World Development* 105: 189–200.
- Fitzgerald, John, Peter Gottschalk, and Robert Moffitt.** 1998. An analysis of sample attrition in panel data: The Michigan Panel Study of Income Dynamics.
- Foster, Andrew D., and Mark. R. Rosenzweig.** 1995. Learning by doing and learning from others: human capital and technical change in agriculture. *Journal of Political Economy* 103(6): 1176–209.
- Foster, Andrew D., and Mark. R. Rosenzweig.** 2010. Microeconomics of technology adoption. *Annual Review of Economics* 2(1): 395-424.
- Fuchs, William, Brett Green, and David Levine.** 2020. Optimal Arrangements for Distribution in Developing Markets: Theory and Evidence. *American Economic Journal: Microeconomics* (forthcoming).
- Goyal, Aparajita.** 2010. Information, direct access to farmers, and rural market performance in central India. *American Economic Journal: Applied Economics* 2(3): 22-45.
- Grimm, Michael, Peter Knorringa, Jann Lay.** 2012. Constrained Gazelles: High Potentials in West Africa's Informal Economy. *World Development* 40(7): 1352-1368.
- IEA (International Energy Agency).** 2020. SDG7: Data and Projections, IEA, Paris <https://www.iea.org/reports/sdg7-data-and-projections>.
- Jensen, Robert.** 2007. The digital divide: Information (technology), market performance, and welfare in the South Indian fisheries sector. *The Quarterly Journal of Economics* 122(3): 879-924.
- Jensen, Robert, and Nolan H. Miller.** 2018. Market integration, demand, and the growth of firms: Evidence from a natural experiment in India. *American Economic Review* 108(12): 3583-3625.
- Jeuland, Marc A., and Subhrendu K. Pattanayak.** 2012. Benefits and costs of improved cookstoves: assessing the implications of variability in health, forest and climate impacts. *PLoS One* 7(2): e30338.
- Jeuland, Marc A., Ousmane Ndiaye, and Faraz Usmani.** 2021. The more choice, the better? Evidence from experimental auctions in rural Senegal. *Economics Letters* 206: 109969.
- Karlan, Dean, and Jonathan Zinman.** 2011. Microcredit in theory and practice: Using randomized credit scoring for impact evaluation. *Science* 332(6035): 1278-1284.
- Keller, Wolfgang.** 2004. International technology diffusion. *Journal of economic literature* 42(3): 752-782.
- Khandker, Shahidur R., Zaid Bakht, Gayatri B. Koolwal.** 2009. The poverty impact of rural roads: Evidence from Bangladesh. *Economic Development and Cultural Change* 57(4): 685-722.

- Lee, David S.** 2009. Training, wages, and sample selection: Estimating sharp bounds on treatment effects. *The Review of Economic Studies*, 76(3), 1071-1102.
- Levine, David I., Theresa Beltramo, Garrick Blalock, Carolyn Cotterman, and Andrew M Simons.** 2018. What impedes efficient adoption of products? Evidence from randomized sales offers for fuel-efficient cookstoves in Uganda. *Journal of the European Economic Association* 16(6): 1850-1880.
- Lewis, Jessica J., Vasundhara Bhojvaid, Nina Brooks, Ipsita Das, Marc A. Jeuland, Omkar Patange, and Subhrendu K. Pattanayak.** 2015. Piloting Improved Cookstoves in India, *Journal of Health Communication* 20(sup1): 28-42.
- Lim, Stephen S., Theo Vos, Abraham D Flaxman, Goodarz Danaei, Kenji Shibuya, Heather Adair-Rohani, ..., and Ziad A. Memish.** 2013. A comparative risk assessment of burden of disease and injury attributable to 67 risk factors and risk factor clusters in 21 regions, 1990–2010: a systematic analysis for the Global Burden of Disease Study 2010. *The Lancet* 380(9859): 2224-60.
- McKenzie, David, and Christopher Woodruff.** 2008. Experimental evidence on returns to capital and access to finance in Mexico. *The World Bank Economic Review* 22(3): 457-482.
- McKenzie, David, and Christopher Woodruff.** 2014. What are we learning from business training and entrepreneurship evaluations around the developing world? *The World Bank Research Observer* 29(1): 48-82.
- Meager, Rachael.** 2019. Understanding the Average Impact of Microcredit Expansions: A Bayesian Hierarchical Analysis of Seven Randomized Experiments. *American Economic Journal: Applied Economics* 11(1): 57–91.
- Mehetre, Sonam A., N.L. Panwar, Deepak Sharma, and Himanshu Kumar.** 2017. Improved biomass cookstoves for sustainable development: A review. *Renewable and Sustainable Energy Reviews* 73: 672-687.
- Minten, Bart, Bethlehem Koru, David Stifel.** 2013. The last mile(s) in modern input distribution: Pricing, profitability, and adoption. *Agricultural Economics* 44(6): 629-646.
- Mitra, Sandip, Dilip Mookherjee, Maximo Torero, and Sujata Visaria.** 2018. Asymmetric information and middleman margins: An experiment with Indian potato farmers. *Review of Economics and Statistics* 100(1): 1-13.
- Mobarak, Ahmed Mushfiq, Puneet Dwivedi, Robert Bailis, Lynn Hildemann, and Grant Miller.** 2012. Low demand for nontraditional cookstove technologies. *Proceedings of the National Academy of Sciences of the United States of America* 109(27): 10815-10820.
- Moser, Christine, Christopher Barrett, and Bart Minten.** 2009. Spatial integration at multiple scales: rice markets in Madagascar. *Agricultural Economics* 40(3): 281-294.
- MPC (Minnesota Population Center).** 2020. Integrated Public Use Microdata Series, International: Version 7.3 [Senegalese National Agency of Statistics and Demography (ANSD): Census data 2013]. Minneapolis, MN: IPUMS, <https://doi.org/10.18128/D020.V7.3>.
- Mu, Ren, and Dominique Van de Walle.** 2011. Rural roads and local market development in Vietnam. *The Journal of Development Studies* 47(5): 709-734.
- Osborne, Theresa.** 2005. Imperfect competition in agricultural markets: evidence from Ethiopia. *Journal of Development Economics* 76(2): 405-428.
- Pattanayak, Subhrendu K., Marc A. Jeuland, Jessica J. Lewis, Vasundhara Bhojvaid, Nina Brooks, Abhishek Kar, ..., and Veerabhadran Ramanathan.** 2016. Cooking up change in the Himalayas: experimental evidence on cookstove promotion. Duke Environmental and Energy Economics Working Paper Series, Working Paper EE 16-03.

- Pattanayak, Subhrendu K., Marc A. Jeuland, Jessica J. Lewis, Faraz Usmani, Nina Brooks, Vasundhara Bhojvaid, ..., and Veerabhadran Ramanathan.** 2019. Experimental evidence on promotion of electric and improved biomass cookstoves. *Proceedings of the national Academy of Sciences*, 116(27): 13282-13287.
- Puzzolo, Elisa, Hisham Zerriffi, Ellison Carter, Harry Clemens, Harry Stokes, Pamela Jagger, and Helen Petach.** 2019. Supply considerations for scaling up clean cooking fuels for household energy in low-and middle-income countries. *GeoHealth* 3(12): 370-390.
- Ramanathan, Veerabhadran, and Gregory R. Carmichael.** 2008. Global and regional climate changes due to black carbon. *Nature Geoscience* 1: 221-227.
- Shindell, Drew, Johan C. I. Kuylensstierna, Elisabetta Vignati, Rita van Dingenen, Markus Amann, Zbigniew Klimont, ..., and David Fowler.** 2012. Simultaneously mitigating near-term climate change and improving human health and food security. *Science* 335: 183–189.
- Smith, Kirk R., Nigel Bruce, Kalpana Balakrishnan, Heather Adair-Rohani, John Balmes, Zoë Chafe, ..., and HAP CRA Risk Expert Group.** 2014. Millions dead: how do we know and what does it mean? Methods used in the Comparative Risk Assessment of Household Air Pollution. *Annual Review of Public Health* 35: 185-206.
- SNV (Netherlands Development Organization).** 2015. Mapping Successful Cookstove Distribution Models: Eight Success Factors to Reach the Last Mile. https://beamexchange.org/uploads/filer_public/e5/0d/e50d9a26-f413-4878-9160-1c48dcb1de4e/mappingcookstoves_distribution.pdf
- Solow, Robert M.** 1956. A contribution to the theory of economic growth. *The Quarterly Journal of Economics* 70(1): 65-94.
- Suri, Tavneet.** 2011. Selection and comparative advantage in technology adoption. *Econometrica* 79(1): 159-209.
- Svensson, Jakob and David Yanagizawa.** 2009. Getting prices right: the impact of the market information service in Uganda. *Journal of the European Economic Association* 7(2-3): 435-445.
- Thakur, Megha, Paulien A. W. Nuyts, Esther A. Boudewijns, Javier Flores Kim, Timor Faber, Giridhara R. Babu, ..., and Jasper V. Been.** 2018. Impact of improved cookstoves on women's and child health in low and middle income countries: a systematic review and meta-analysis. *Thorax* 73(11): 1026-1040.
- Van Kirk, Greg.** 2010. The MicroConsignment Model: Bridging “the Last Mile” of Access to Products and Services for the Rural Poor. *Innovations* 5(1): 101-127.
- Van Rooyen, Carina, Ruth Stewart, and Thea De Wet.** 2012. The impact of microfinance in sub-Saharan Africa: a systematic review of the evidence. *World Development* 40(11): 2249-2262.
- Vickrey, William.** 1961. Counterspeculation, auctions, and competitive sealed tenders. *The Journal of Finance* 16(1): 8-37.
- Wathore, Roshan, Kevin Mortimer, and Andrew P. Grieshop.** 2017. In-use emissions and estimated impacts of traditional, natural-and forced-draft cookstoves in rural Malawi. *Environmental science and technology* 51(3): 1929-1938.
- WFP (World Food Programme) Senegal.** 2017. Safe Access to Fuel and Energy Senegal. World Food Programme, Rome. <https://www.wfp.org/publications/2017-safe-access-fuel-and-energy-initiative-senegal>
- Williamson, Oliver E.** 1979. Transaction-cost economics: The governance of contractual relations. *Journal of Law and Economics* 22: 233–261.

Appendix Chapter 2

Appendix 2A: Introduction

Table 2A.1: List of deviations from Pre-Analysis Plan

Figure 2.4 and section 2.7.6: We announced monthly mobile phone data collection until June 2019. Thanks to additional funding, we prolonged monthly data collection until October 2019 and conducted two additional rounds of data collection to measure long-term impacts in 2021. Accordingly, also in-person endline data collection shifted from June 2019 to November 2019. This also implies that all analyses of long-term impacts were not announced in the PAP; yet they follow the specifications announced in the PAP.

Section 2.7.4:

We test for the robustness of our results towards heterogenous regularity in reporting even though it is not announced in the PAP. The obvious need for this analysis became apparent only after seeing very heterogenous response rates.

We announced to impute missing dependent variables (monthly firewood Jambar sales). This is obsolete given the nature of our data collection, which asks for sales since the last call and thereby retrieves all sales in the analysis of sales in the main monitoring period.

In analysis of sales in the long-term period, we replace missing dependent variables by their all-time maximum sales number instead of imputing them. We do so to be conservative.

We announced to correct for attrition that is higher than five percent following Fitzgerald et al. (1998) and Lee (2009). While balanced across experimental groups, attrition is higher than five percent at endline, potentially affecting the analyses of two outcomes: a) uptake of marketing materials in Table 4 and b) firewood Jambar sales in a typical month in Annex Table E. 2. As both corrections do not apply to these analyses, as they are non-panel data statistics, we instead apply alternative corrections using bounding exercises.

Table 2.4: We announced to test for the impact of our treatments on the use of multiple marketing materials (as secondary outcomes). This included five outcomes that ask directly for use of our treatment elements (e.g., use of posters).

- Our survey question on the outcome “whether vendors contacted village chiefs” was ambiguous and therefore excluded from the analysis.
- The PAP listing was incomplete in that it did not list two elements of our treatments (whether T-shirts are used for marketing and whether vendors used transport grant). Note that the PAP mentions the two elements in other contexts. We include these outcomes in the analysis for completeness.
- We add the outcomes “any marketing activity” and “any intervention marketing tool” as aggregate outcomes, which had not been announced in the PAP.

We announced to use 12 business and vendor characteristics in balance checks. To benefit from our extensive baseline survey and provide contextual information, we add additional variables to the balancing.

Section 2.7.3: We provide analysis on the heterogeneity of impacts across individual vendors and regions. These analyses were not announced in the PAP but later turned out to be highly important for assessing our intervention’s impacts transparently. However, these analyses are purely descriptive.

Note: To enhance transparency of our analysis, we pre-registered this study in the Registry for International Development Impact Evaluations (RIDIE) under RIDIE-STUDY-ID-59c9e0f49a591 in September 2017. The pre-Analysis plan (PAP) was published in March 2019 prior to endline data collection. We adhere to the PAP throughout the paper. Yet, we deviate in some aspects when only after endline data collection announced procedures proved unreasonable/impossible or non-announced procedures proved reasonable/possible. This table lists all deviations and provides our rationale behind them.

Appendix 2B: Intervention

Figure 2B.1: Village demand leaflet (anonymized)

Contacte: Kofi Annan (7777777)

Desmond Tutu (ID: 2; Tél: 7777777) — Louma: Commune, Department			
	↑ 7 000 CFA		
Village			
Commune			
Department			
454			
Ellen Johnson Sirleaf 77777777		15 000 CFA	13
Village			
Commune			
Department			
856			
Wangari Maathai 77777777		10 000 CFA	10
Village			
Commune			
Department			
687			
Abiy Ahmed 77777777		10 000 CFA	12
Village			
Commune			
Department			
844			
Nelson Mandela 77777777		12 500 CFA	11
Village			
Commune			
Department			
462			
Denis Mukwege 77777777		15 000 CFA	6
Village			
Commune			
Department			
408			
Tawakkol Karman 77777777		15 000 CFA	7
Village			
Commune			
Department			
634			
Mohammed el-Baradei 77777777		10 000 CFA	12

Source: Own presentation.

The demand sheet conveys the following information:

- the highest bid for the firewood *Jambar* as displayed by the figure with two outstretched arms in Figure 2B.1;
- the share of auction participants willing to pay more than XOF 7,000 or USD 12.30 (the firewood *Jambar*'s approximate retail price) as displayed by the share of black figures relative to white figures;
- the extrapolated total number of households willing to pay more than USD 12.30 (i.e., share of participants who bid above times the village's population) as displayed by house figure;
- the contact information of a local village authority displayed on the left; and
- the village population, as displayed on the left in Figure 2B.1.

Figure 2B.2: Marketing elements

A: T-Shirt with firewood Jambar logo



B: FASEN DinA4 leaflet with do's and don't on stove use




C: FASEN DinA3 poster



Note: prior to our experiment the marketing materials were developed, piloted and used by FASEN to support its outreach activities with Jambar producers.








Appendix 2C: Data













Figure 2C.1: Vendor log sheet for bookkeeping



FICHE DE VENTE DES FOYERS

Nom du commerçant : _____ Nom et Numéro en cas de question : _____

A	B	C	D	E	F	G
Sakkanal	Jambar à bois	Jambar à charbon	Malgache	Bili	Bili Amélioré	Taaru
						

Nom du village / ville du client	Nom de la région du client	Nom et prénom du client	Numéro de téléphone du client	Date de vente	Quantité des Foyers vendu	Type de Foyer vendu	Endroit de vente			Payement	
							Sur le Louma	Au village	En ville	Payement directe	Tranches
											
Nguene	Louga	Fatima SYLLA	338298564	25.8.2017	3 xxx	A A C		x		x	

Note: On top, the vendor log sheet features a list of the most important traditional and improved stoves that are available on Senegalese rural markets. Below, vendors fill-out one row per client who bought a wood stove(s). The first entry is a non-existing example for explication purposes. The sheet was designed after consultations with local partners and extensive piloting. Field teams also conducted demonstrations and practice rounds with vendors to provide an overview of how to record sales, underscoring any language could be used to complete the sheet. The goal of these log sheets was to facilitate vendors' self-tracking of their sales and to ease recall burden. In particular, in designing these sheets we aimed to ensure that vendors who were numerate, but illiterate could easily use the sheets to track their sales.

Figure 2C.2: Producer log sheet for bookkeeping



**FICHE DE VENTE D'ÉTUDE
FOYERS AMÉLIORÉS À BOIS**



Nom du forgeron : _____

Nom et Numéro en cas de question : [REDACTED] [REDACTED]

Numéro de téléphone du client	Nom et prénom du client	Nom du village / ville du client	Nom de la région du client	Date de vente	Quantité des Foyer amélioré vendu			Type de client				
					Jambar JEGG (4kg)	Jambar JABOOT (7kg)	Jambar JONGOMA (15kg)	Client individuel	Vendeur marché	Commerçant Louma	Groupement de femmes	Autre, spécifiez
338298564	Ousmane SYLLA	Nguene	Louga	25.8.2017	3 X X X		1 X		X			

Note: The producer log sheet tracked sales of firewood Jambar of 4kg, 7kg, and 15kg. The last rows capture whether the client is an end-user, a vendor on fixed markets, or a vendor on weekly markets, a women's group or other. Retailers that resell on both weekly and fixed markets are categorized as weekly market vendors, i.e., they at least sometimes sell on weekly markets. Women groups are always categorized as women groups, independent of whether they resell the stove.

Figure 2C.3: Share of vendors reporting sales, by experimental group and month of call

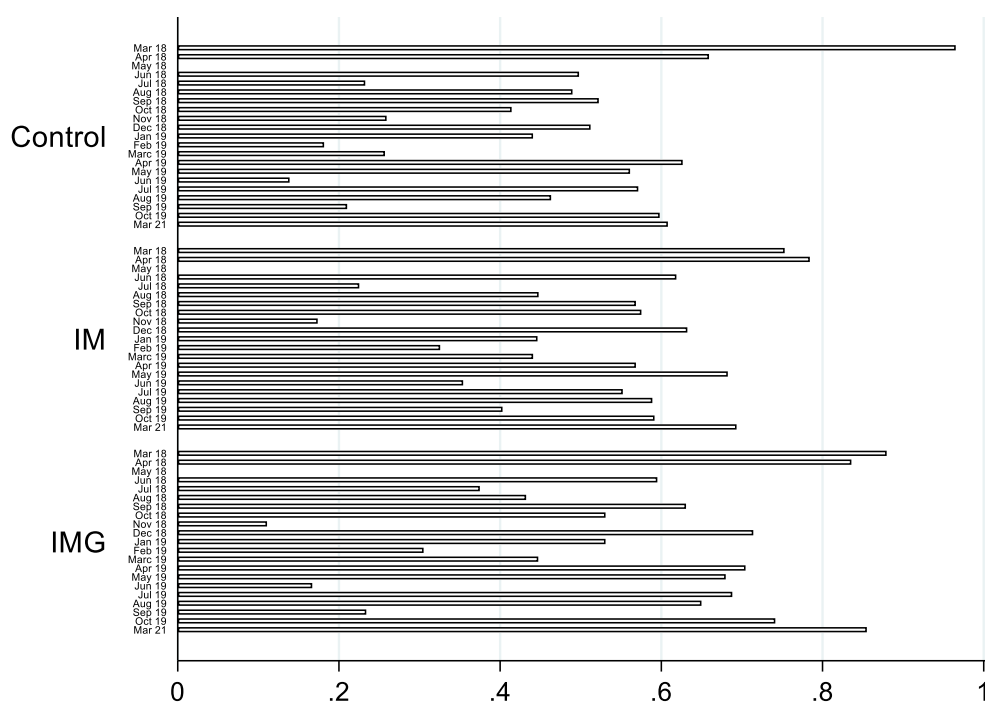


Figure 2C.4: Total number of reporting months, by vendor

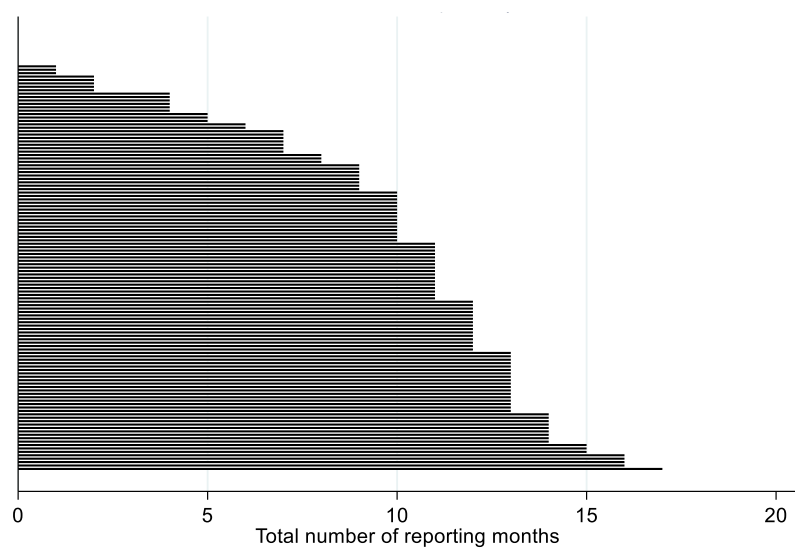


Table 2C.1: Balancing of vendor and business characteristics, at baseline

	(1)	(2)	(3)	(4)	(5)
	Control	IM	IMG	All	p-val from ANOVA
	Mean	Mean	Mean	Mean	Mean
Vendor and business characteristics					
Age	41.61	39.60	41.06	40.65	0.69
Male	0.61	0.67	0.69	0.66	0.79
No education/ Koranic school	0.61	0.69	0.67	0.66	0.79
Reported revenues in USD	2771.09	3189.84	1868.30	2588.15	0.25
Business growth 12months: negative	0.06	0.13	0.06	0.09	0.49
Business growth 12months: constant	0.13	0.08	0.15	0.12	0.63
Business growth 12months: growth	0.81	0.79	0.79	0.80	0.98
Number of loumas	3.00	2.96	3.08	3.02	0.94
Days in loumas (monthly)	20.87	21.10	19.81	20.56	0.75
Has a bank account	0.35	0.46	0.44	0.43	0.65
Credit in last 12 months	0.48	0.60	0.48	0.53	0.41
Has a debtor	0.81	0.85	0.85	0.84	0.82
Offers credit/installments	0.90	0.96	0.92	0.93	0.60
Employees	0.97	0.85	1.02	0.94	0.84
Collaborates with stove vendors	0.42	0.33	0.35	0.36	0.74
Source of ICS: city wholesaler	0.39	0.35	0.33	0.35	0.89
Source of ICS: louma distributor	0.03	0.04	0.08	0.06	0.55
Source of ICS: producer	0.16	0.17	0.13	0.15	0.83
Producers buying Jambars from	0.42	0.35	0.46	0.41	0.83
Prefers present pay-off	0.90	0.75	0.94	0.86	0.02**
Impression: entrepreneurial ambitions	0.48	0.48	0.54	0.50	0.81
Outreach barriers: locations unknown	0.06	0.04	0.10	0.07	0.49
Outreach barriers: no liquidity/credit	0.23	0.23	0.17	0.20	0.71
Outreach barriers: transport cost	0.16	0.31	0.29	0.27	0.30
Outreach barriers: low demand	0.03	0.06	0.10	0.07	0.46
Outreach barriers: no interest	0.42	0.17	0.29	0.28	0.05**
Importance of Jambar in business revenues: none	0.35	0.46	0.44	0.43	0.65
Importance of Jambar in business revenues: low	0.19	0.17	0.23	0.20	0.75
Importance of Jambar in business revenues: medium	0.32	0.21	0.21	0.24	0.43
Importance of Jambar in business revenues: high	0.13	0.17	0.13	0.14	0.82

Pre-intervention average monthly stove sales

Jambar	0.07	0.04	0.13	0.08	0.59
Charcoal Jambar	2.37	2.26	2.31	2.31	0.99
Sakkanal (ICS))	0.02	0.01	0.14	0.06	0.20
Basic metal stove 1	1.00	0.21	0.71	0.59	0.18
Basic metal stove 2	0.20	0.20	0.34	0.25	0.81
Bili amélioré (ICS)	0.10	0.05	0.20	0.12	0.32

Marketing activities

Marketing brochures	0.03	0.02	0.00	0.02	0.50
Radio/TV marketing	0.06	0.02	0.08	0.06	0.40
SMS marketing	0.00	0.02	0.00	0.01	0.44
Online marketing	0.06	0.06	0.04	0.06	0.88
Whatsapp marketing	0.00	0.04	0.06	0.04	0.38
Makes wall paintings	0.00	0.02	0.00	0.01	0.44
Household visits	0.06	0.04	0.10	0.07	0.49
Stove demonstrations	0.03	0.02	0.00	0.02	0.50
Word-of-mouth marketing	0.29	0.29	0.40	0.33	0.48
Tontines	0.03	0.04	0.00	0.02	0.39
Any marketing activity	0.39	0.40	0.48	0.43	0.64
N	31	48	48	127	127

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

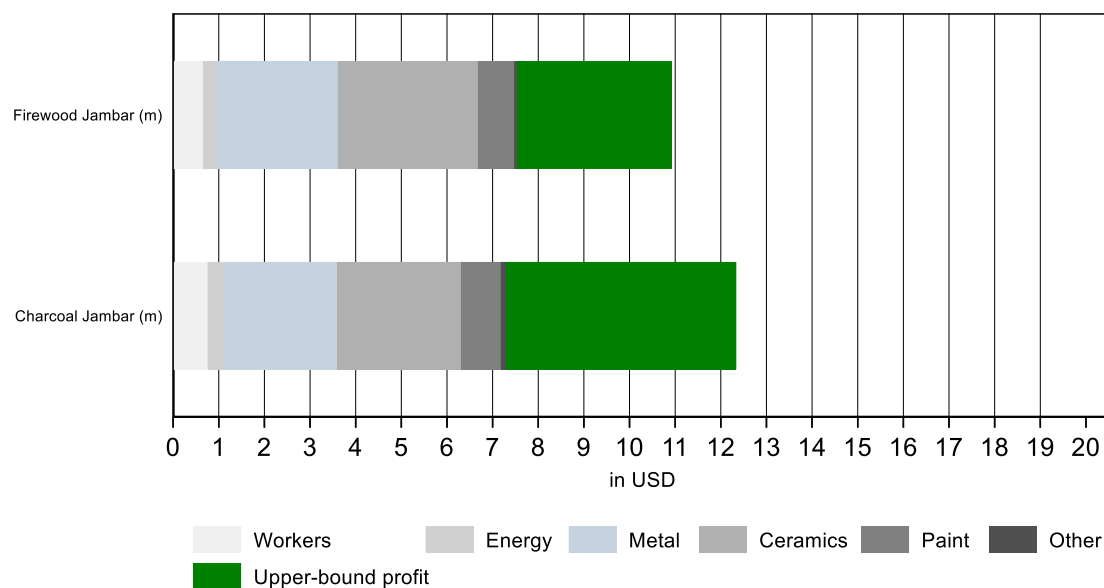
Table 2C.2: Socio-economic producer characteristics, at baseline

	Mean	Standard deviation
Age (#)	37.77	10.04
Literacy (d)	0.39	
Active since (year, #)	2002.10	9.84
Employees (#)	2.65	2.62
Business value (USD)	9090.56	23822.11
Bank account (d)	0.43	
Loan last 12 months (d)	0.29	
Member producer association (d)	0.66	
Sales: Charcoal Jambar (#)	44.61	91.00
Sales: Firewood Jambar (#)	10.29	30.17
Sales: Pots and kitchenware (#)	12.74	170.61
Sales: Censer (#)	7.33	29.47
Expansion to new markets (d)	0.73	
N	215	

Note: d = “dummy”; # = “number of.”

Appendix 2D: The Jambar market

Figure 2D.1: Components of the Firewood Jambar retail price, as reported by producers at baseline



Note: m=medium. Profits abstracts from fixed and some variable costs. The full bar shows producers' average retail prices. This data has substantial missing values, as producers could chose for which type (charcoal or firewood) to report, and many producers abstained from reporting their stove retail prices. The calculations hence rely on a small number of observations, namely 10 for the firwood Jambar and 83 for the charcoal Jambar.

Appendix 2E: Robustness

Table 2E.1: Impact of the intervention on vendors' marketing, any treatment group

	(1) Used Jambar T- shirt	(2) Displayed Jambar poster	(3) Conducted village sales visit(s)	(4) Contacted producers	(5) Conducted stove demon.	(6) Used transport grant	(7) Any intervention marketing tool	(8) Any marketing tool	(9) Any marketing tool
Any treatment	0.44*** (0.087)	0.52*** (0.074)	0.047** (0.023)	0.24*** (0.047)	0.077 (0.064)	0.077 (0.064)	0.64*** (0.086)	0.050 (0.10)	
Post								0.057 (0.12)	0.037 (0.12)
Any treatment X Post								0.33** (0.14)	0.38*** (0.14)
N	113	113	113	113	113	113	113	240	226
Control/pre- intervention mean ^o	0.15	0.074	0	0	0.074	0.074	0.19	0.43	0.43
Adjusted R-sq.	0.14	0.19	0.0026	0.063	0.00046	0.00046	0.33	0.14	0.20
Vendor FEs	No	No	No	No	No	No	No	No	Yes

*Note: Standard errors (in parentheses) robust to heteroskedasticity; standard errors clustered at the vendor level in columns (8) and (9). Singletons omitted from estimation in column (9). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The marketing elements in (1)-(5) are specific to the intervention and were only provided to treatment vendors. By construction, rates of use of these marketing elements in the control group are zero. ^oShows control means for columns (1)-(7), and control baseline means for columns (8) and (9).*

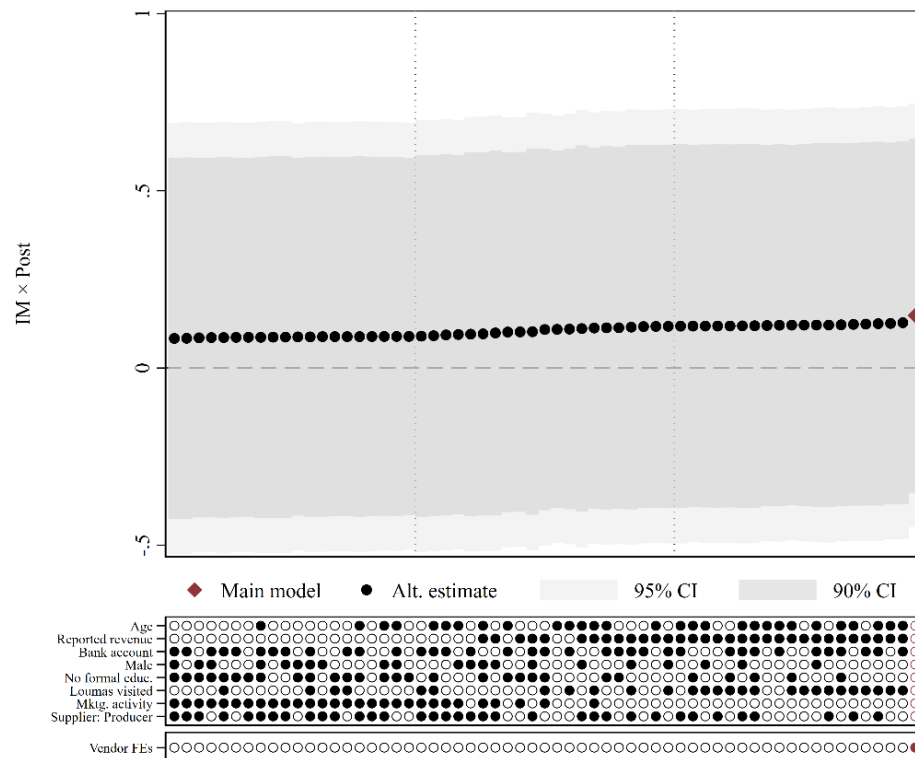
Table 2E.2: Impact of the intervention on vendors' typical monthly sales

	(1) Typical monthly sales	(2) Typical monthly sales
Any treatment	1.71*** (0.57)	
IM		0.036 (0.61)
IMG		3.24*** (1.10)
Constant	0.57 (0.47)	0.57 (0.47)
N	110	110

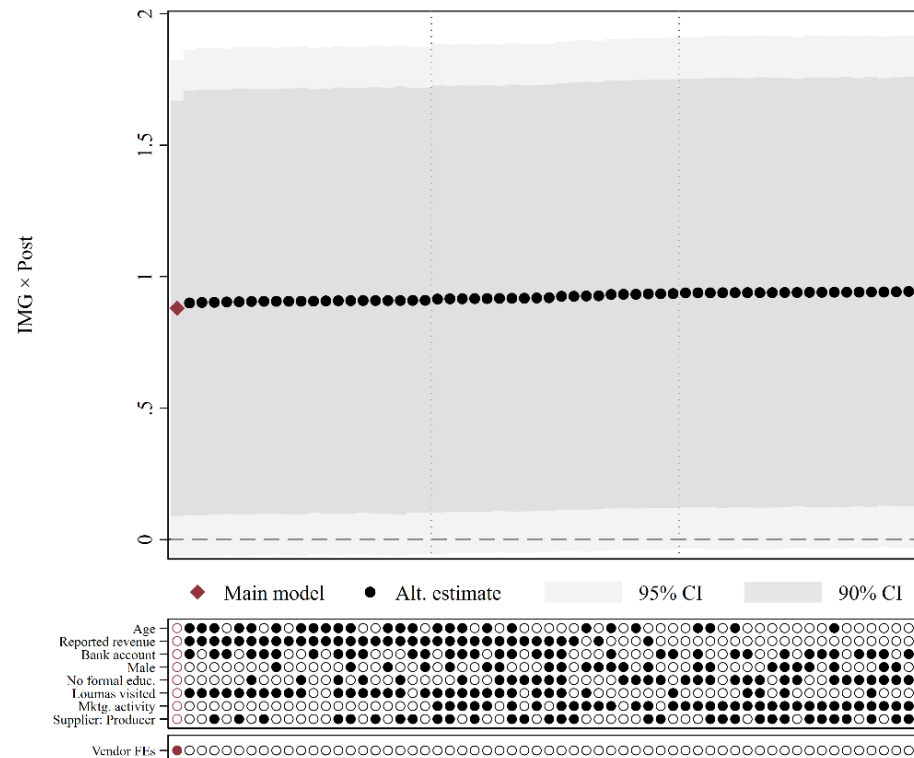
Note: Standard errors (in parentheses) clustered at the louma level.

Figure 2E.1: Robustness of the main results to sequential inclusion of control variables

A: Information-Marketing (IM) treatment



B: Information-Marketing-Grant (IMG) treatment



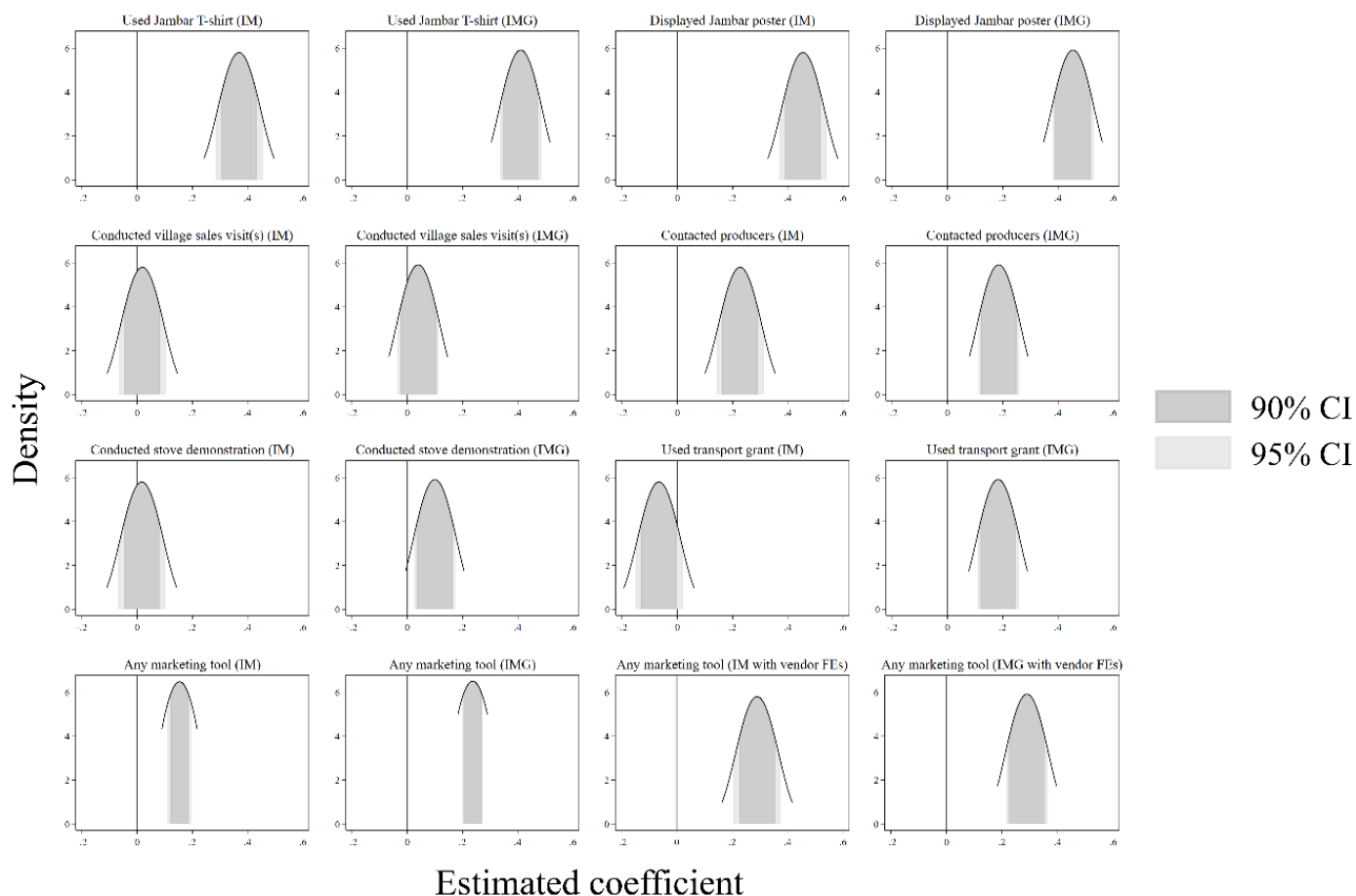
Note: The figures show that sequential inclusion of control variables to our main regression (Table 2.4) does not alter our results. Panel A and B plot the estimated coefficients for IMxPOST and IMGxPOST based on around 250 regressions with different permutations/combinations of a set of control variables (which are also included in our balance test in Appendix Figure 2C.1Table 2C.1). The panels below the figures show the controls included in each specification. For a better overview, the figures show a subsample of 60 estimates (20 of the lowest ones on the left, 20 of the highest ones on the right, and 20 randomly selected ones from the middle).

Table 2E.3: Robustness of main results to outliers

	(1) Natural log	(2) Natural log	(3) Winsorized 95%	(4) Winsorized 95%	(5) Winsorized 99%	(6) Winsorized 99%	(7) Trimmed 95%	(8) Trimmed 95%	(9) Trimmed 99%	(10) Trimmed 99%
Any treatment X Post	0.38 (0.28)		0.067 (0.084)		0.44 (0.29)		0.065*** (0.020)		0.24 (0.25)	
IM X Post		0.19 (0.31)		0.013 (0.083)		0.10 (0.29)		0.047** (0.019)		0.064 (0.27)
IMG X Post		0.57* (0.33)		0.12 (0.10)		0.77* (0.43)		0.084** (0.036)		0.42 (0.32)
N	2667	2667	2667	2667	2667	2667	2594	2594	2649	2649

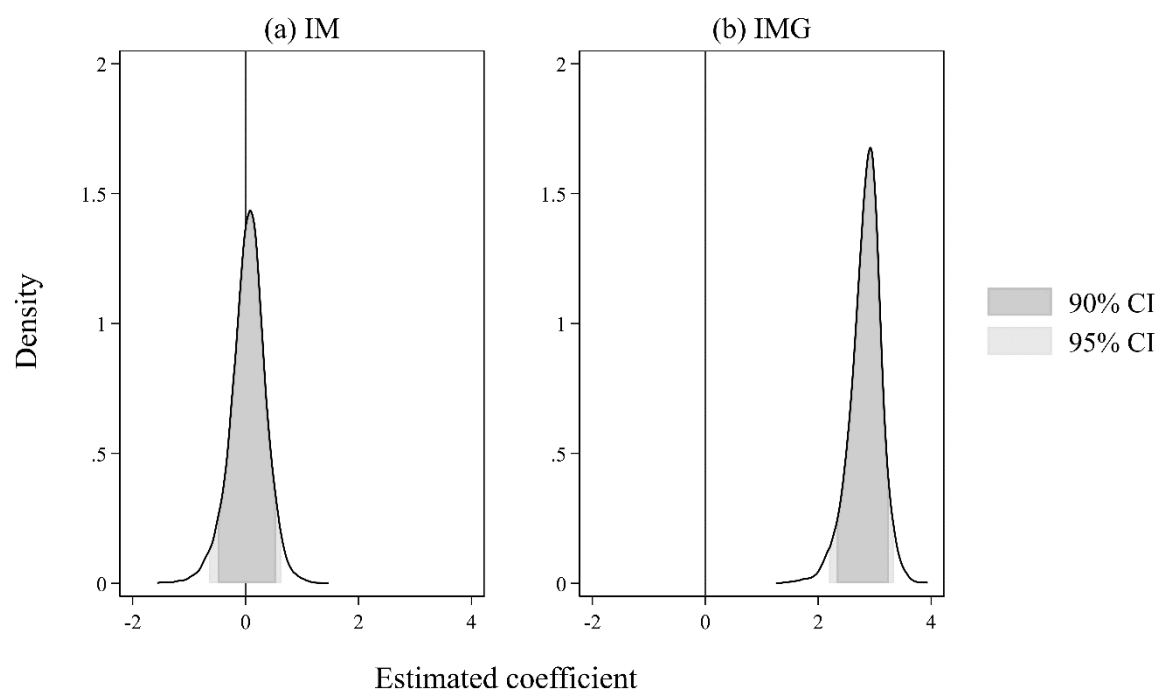
*Note: Standard errors (in parentheses) clustered at the vendor level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table tests for robustness of our main results to taking the natural log of sales, winsorizing and trimming the upper 5 and 1 percent of sales. In columns (7) and (8), also the IM treatment and the pooled treatment becomes significant when trimming the upper 5 percent, as we drop all control vendors who sell the firewood Jambar, thereby reducing the control mean to zero, making any sales in the treatment groups statistically distinguishable from the control mean of zero.*

Figure 2E.2: Impact of the intervention on vendors' marketing by experimental group, correcting for endline attrition using bounding exercise



Note: All outcomes in the analysis of marketing uptake are binary. We consider all $2^{14} = 16,384$ combinations of values that the 14 attrited vendors' marketing outcomes can take, covering all possible scenarios of what the missing values, i.e., marketing activities of 14 vendors, may have been. The figure shows the distribution of the estimated coefficients when re-running our main analysis under each of these assumptions. The grey areas show the 90 and 95 percent confidence intervals. The analysis shows that our results are roughly robust to all possible assumptions about attritors' marketing activities at endline, i.e., most CIs do not cross the zero-line and are hence statistically different from zero. The only exception is the conduct of village sales visits, which was borderline significant for the IMG group in our main analysis and is no longer significant under these assumptions about attritors' marketing activities.

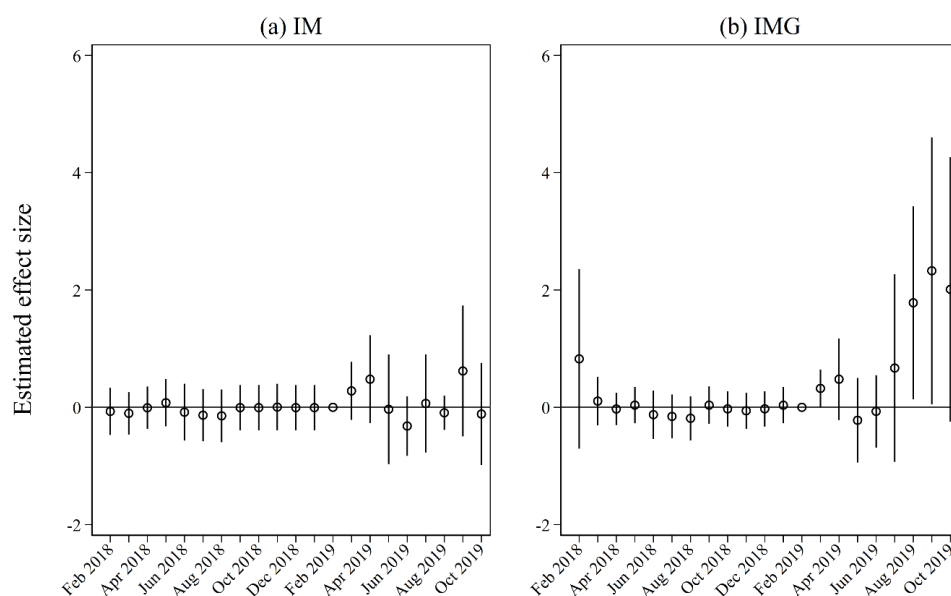
Figure 2E.3: Impact of the intervention on vendors' typical monthly sales of the firewood Jambar, correcting for endline attrition using bounding exercise



Note: We lack data on vendors' self-reported typical monthly sales for 17 out of 127 vendors. We use a simulation-based approach to assess the degree to which these missing values affect our results. Specifically, we replace the missing values for these vendors with draws from a $\text{Gamma}(0.456, 5)$ distribution, whose mean value and shape broadly resemble the distribution of typical monthly sales reported by the remaining 110 vendors. We then repeat the analyses shown in column 2 of Table E. 1 a total of 10,000 times to obtain a distribution of estimated coefficients for IM (panel a) and IMG (panel b) vendors, which we use to evaluate statistical significance.

Appendix 2F: Impact heterogeneity

Figure 2F.1: Month-by-month impact of the intervention on monthly firewood Jambar sales, by treatment group



Note: This figure plots estimated values of $\hat{\beta}_1$ (panel a) and $\hat{\beta}_2$ (panel b) from equation (3) with standard errors clustered at the vendor level. Error bars represent 90 percent confidence intervals. Each coefficient represents the differential impact on sales by treatment vendors relative to February 2019, the month immediately prior to the launch of the intervention (omitted to avoid perfect multicollinearity).

Table 2F.1: Characteristics of survey regions

	Diourbel	Fatick	Kaffrine	Kaolack	Louga	Saint Louis	Thiès	Average	Total
# of FASEN producers	36	19	20	58	11	9	23	25.1	176*
Producer density (per 1000km ²)°	7.5	2.8	1.8	10.8	0.4	0.5	3.4	3.9	
Average demand in WTP surveys (in USD)	4.3	5.0	5.3	6.5	3.7	4.6	4.5	4.8	
Median demand in WTP surveys (in USD)	4.3	4.3	4.3	4.3	3.5	3.9	0.7	3.6	
# of all loumas	18	18	22	16	26	16	14	18.6	130
# of surveyed loumas*	8	10	8	10	6	1	8	7.3	51
# of all vendors in surveyed loumas	37	42	23	51	29	9	30	31.6	221
# of surveyed vendors	19	24	20	31	13	3	17	18.1	127
Population (in thousands) °	1,420	685	544	918	835	871	1,709	997.5	6,982
Population density°	294	100	48	171	34	45	256	135.6	
Rural population share (in %)°	84	84	84	64	78	54	51	71.3	

*Note: *excludes Dakar-based producers; *excludes loumas where no new vendors were willing/ available to participate in the survey; °Source: ANSD (2014).*

Appendix 2G: Impacts on upstream producers' sales

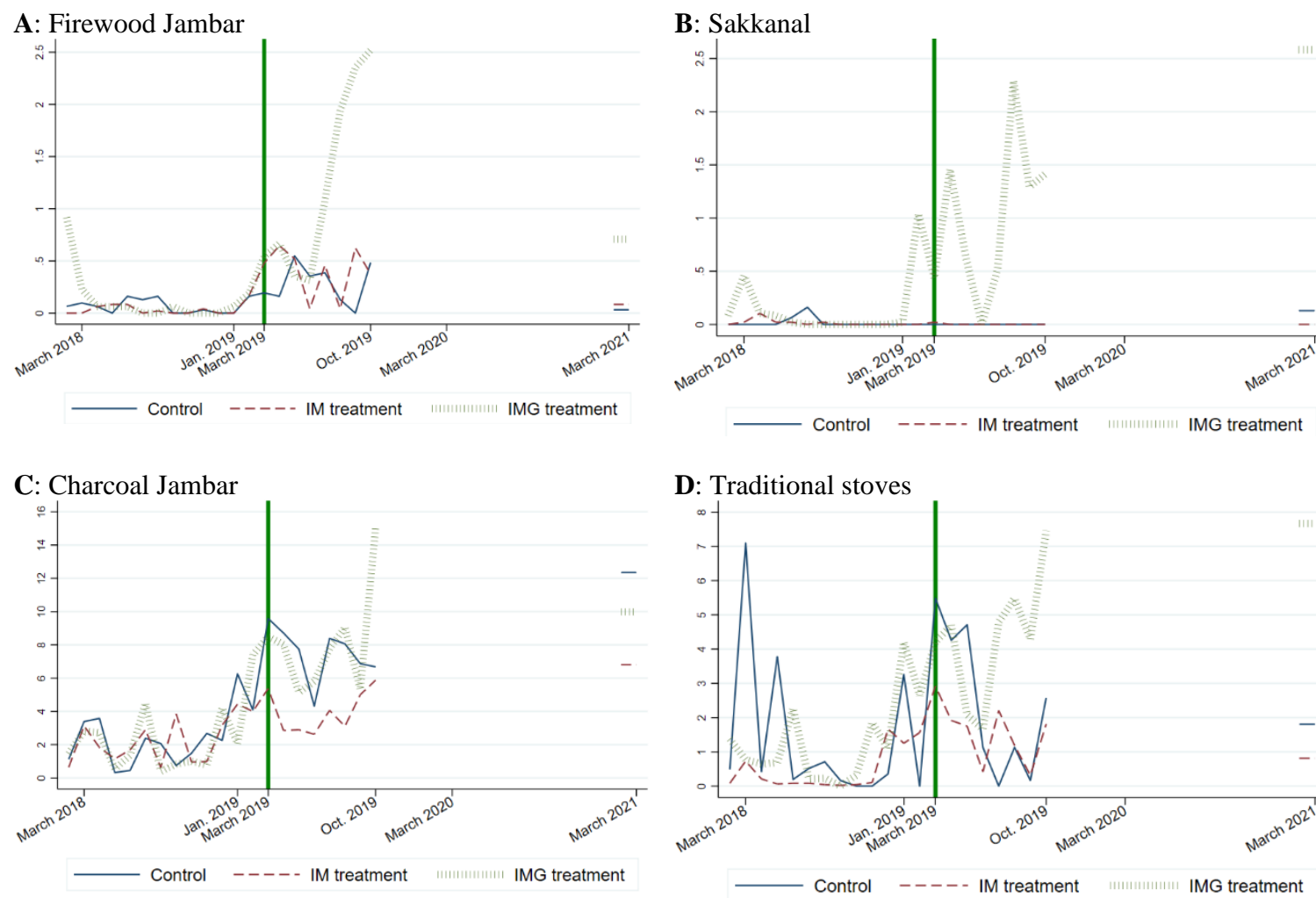
Table 2G.1: Impact of the intervention on sales volume by producers and on joint sales volume by producers and vendors

	Producers				Producers and vendors
	(1) 4kg firewood Jambars sold	(2) 7kg firewood Jambars sold	(3) 15 kg firewood Jambars sold	(4) All firewood Jambars sold	(5) All firewood Jambars sold
Post intervention	0.032 (0.13)	-0.24 (0.85)	0.14 (0.27)	-0.065 (1.09)	155.0 (153.3)
Producer Fes	Yes	Yes	Yes	Yes	—
Month FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
N	3013	3013	3013	3013	20

Note: Standard errors (in parentheses) clustered at the level of the city in which the producer is based in columns (1)-(4) and at the month level in column (5).

Appendix 2H: Impacts on vendor's louma-level sales of other stoves

Figure 2H.1: Vendors' average monthly sales over time in the long run, by experimental group and stove type



Note: Y-axes differ; the green line indicates the timing of the intervention.

Table 2H.1: Impact of the intervention on monthly sales of other stove types, by experimental group and time period (main monitoring and long-term)

	(1) Firewood Jambars	(2) Firewood Jambars	(3) Firewood Jambars	(4) Firewood Jambars	(5) Charcoal Jambars	(6) Charcoal Jambars	(7) Charcoal Jambars	(8) Charcoal Jambars	(9) Sakkanals	(10) Sakkanals	(11) Sakkanals	(12) Sakkanals	(13) Trad. stoves	(14) Trad. stoves	(15) Trad. stoves	(16) Trad. stoves
Any treatment X Post	0.46 (0.28)	0.47* (0.26)			-1.26 (2.05)	-1.86 (2.14)			0.39 (0.24)	0.45* (0.27)			0.95 (1.49)	0.081 (1.64)		
IM X Post			0.14 (0.27)	0.19 (0.29)			-3.06 (2.03)	-3.45 (2.12)			0.0053 (0.016)	-0.0079 (0.021)			0.31 (1.52)	-0.69 (1.69)
IMG X Post			0.78* (0.42)	0.76* (0.38)			0.53 (2.36)	-0.27 (2.42)			0.77 (0.48)	0.91* (0.52)			1.60 (1.73)	0.86 (1.85)
N	2794	2921	2794	2921	2794	2921	2794	2921	2794	2921	2794	2921	2794	2921	2794	2921
Pre- intervention mean	0.078	0.078	0.078	0.078	2.31	2.31	2.31	2.31	0.062	0.062	0.062	0.062	1.11	1.11	1.11	1.11
Adjusted R- sq.	0.11	0.12	0.12	0.12	0.24	0.26	0.25	0.26	0.12	0.14	0.12	0.14	0.15	0.16	0.15	0.16
Year-month FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Vendor FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period	ST	LT	ST	LT	ST	LT	ST	LT	ST	LT	ST	LT	ST	LT	ST	LT
Attrition adjustment	n.a.	Maximum	n.a.	Maximum	n.a.	Maximum	n.a.	Maximum	n.a.	Maximum	n.a.	Maximum	n.a.	Maximum	n.a.	Maximum

*Note: Standard errors (in parentheses) clustered at the vendor level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. ST= shorter-term (regular monitoring period); LT=longer term (including sales from 2021). To adjust for non-balanced attrition at long-term data collection in 2021, we apply the conservative approach and replace sales of attritors by their all-time maximum monthly sales. This approach is conservative as it assumes the upper-bound of sales for attritors, of which there are most in the control group.*

3 Housing ventilation and air pollution from biomass cooking

Single-authored

3.1 Introduction

Over thirty percent of the world population, or 2.8 billion people, cook with solid fuels such as wood, charcoal, or dung (IEA et al., 2020). The resulting household air pollution (HAP) is the leading environmental cause of mortality, annually causing an estimated 3.8 million premature deaths from strokes, ischemic heart disease, respiratory tract cancers, and obstructive pulmonary diseases (WHO 2016). Women are especially affected, and children, the elderly, and pregnant women are particularly vulnerable. In addition to health costs, traditional cooking with solid fuels and inefficient cooking stoves poses a heavy burden on forests and their ecosystem services, strain women's time and opportunities, and produce emissions that contribute to global climate change.

This chapter proposes improved housing ventilation as a critical, transitory solution on the path towards universal *clean* cooking. Improved housing ventilation refers to permeable walls and roofs, more windows and other openings, and the use of hoods, chimneys in the roof, or fans. The rationale is straightforward. Keeping emissions constant, better ventilated housing will reduce the concentration of HAP, and in turn people's exposure to pollution. Unventilated kitchen walls covered by black soot in solid fuel-reliant homes are often highly suggestive of such a relationship. I substantiate the validity of this claim both by means of a systematic review of the scattered evidence, and by an analysis of rich household data from rural Senegal. This setting is remarkably suitable for this analysis given that traditional cooking is predominant and ventilation conditions vary substantially across households.

Since the 2000s, the international community has responded to the multiple threats of traditional cooking with heavy investments into the dissemination of *improved* and *clean* cookstoves (ICS). Likewise, the government of Senegal has declared diffusion of cleaner energy technologies a political priority (MEDER 2015). The governmental ICS programme Foyers Améliorés au Senegal (FASEN) alone has promoted close to 1.5 million so-called *Jambar* ICS from 2006-2020.

Despite massive efforts, progress in increasing clean cooking has been slow and unsteady over the past decade and across regions, making transitory solutions necessary. Many countries are well off track from achieving universal access to clean cooking by 2030 (Sustainable Development Goal 7), especially in Sub-Saharan Africa (SSA), where population growth has outpaced uptake of cleaner technologies. In rural Senegal, for example, 95 percent of the population still use solid cooking fuels (IEA et al., 2020).

Challenges to the dissemination of ICS include underdeveloped supply chains (Lewis et al. 2015, Pattanayak et al. 2016), misalignment of consumer preferences with available improved technologies, low valuation of the benefits these solutions provide (Mobarak et al. 2012, Jeuland et al. 2015, Jeuland et al. 2014, Jeuland and Pattanayak 2012), liquidity constraints or affordability (Levine et al 2018, Bensch and Peters 2020, Bensch et al. 2015), and poor durability or sustainability (Hanna et al. 2016). Many challenges are aggravated in rural areas due to poverty, lower fuel scarcity (Jagger and Perez-Heydrich 2016), and shallow markets (Lewis and Pattanayak 2012, Jeuland et al. 2015).

As a benchmark for safe air quality, the World Health Organization (WHO) air quality guidelines define that 24-hours PM_{2.5} concentrations are not to exceed 25 µg/m³ for both indoor and outdoor environments and define three interim targets (IT 1-3) for daily concentrations of 37.5 µg/m³, 50 µg/m³, and 75 µg/m³ (WHO 2006). Based on the existing evidence, a violation of the least demanding IT 3, for example, is associated with a five percent increase in short-term mortality (WHO 2006). In line with persistent traditional cooking practices, in many cases, actual HAP in the global south exceed these targets by far (Pope et al., 2017).

This chapter begins with a pre-registered systematic review of the scientific literature on housing ventilation and cooking-related air pollution in low- and middle-income countries. Systematic searches in 13 databases identified 59 papers that assess either particulate matter (PM) or carbon monoxide (CO), the two air pollutants most damaging to human health (WHO 2008). Health and environmental sciences have studied the relationship between kitchen ventilation and air pollution or personal pollution exposure, and, in the aggregate, suggest that HAP is negatively related to ventilation. However, there is little consensus on how to measure ventilation and sample sizes are often small (also see Barnes 2014⁸⁵). The share of studies that find significant pollution reductions from ventilation is similar to the shares found in a recent

⁸⁵ Barnes (2014) warrants that the studies are methodologically weak and insufficiently theoretically founded. He assesses 10 field and laboratory studies that introduce behavioural change strategies to reduce HAP exposure. Four of the behavioural interventions induced better ventilation and reduced indoor PM pollution by between 57 and 98 percent.

systematic review of the impacts of non-chimney, *improved* stoves (Pope et al. 2021). Yet, in stark contrast to housing ventilation, such stoves are a highly prominent policy tool to reduce cooking-related HAP.

Second, this chapter quantifies the influence of kitchen ventilation on PM_{2.5} HAP – or more specifically *kitchen* pollution –, and women’s PM_{2.5} pollution exposure. Both outcomes are measured during monitoring periods of 24 hours among 244 distinct households in 15 rural communities in northern and central Senegal. The pooled ordinary least squares (OLS) analysis aggregates two rounds of detailed panel data from a pre-registered experiment in 2018 and 2019, resulting in 419 household-year observations with measurement of women’s pollution exposures and 220 household-year observations with measurement of kitchen pollution. I use a regression model with rich controls, apply multiple housing ventilation indicators, define pollution both as the 24-hour average and as pollution percentiles across the day, and explore impacts for the reduced sample of open air cooking households. I moreover assess the role of unobservables using the Oster method (Oster 2019). Importantly, while my analysis overcomes major limitations of the existing evidence, it does not necessarily imply causation.

In my kitchen pollution analysis, I find that average PM_{2.5} pollution exceeds the WHO’s safe levels by a large amount (474 µg/m³ versus 25 µg/m³, see WHO 2006). Cooking in *fully* ventilated kitchens (i.e., open air) is associated with 67-82 percent less kitchen pollution relative to *unventilated* kitchens (no opening except for door). *Substantially* ventilated kitchens (semi-enclosed, for example with two or three walls) have between 33-56 percent less pollution (PM_{2.5}). Both associations are statistically significant. My findings suggest that even gradually better ventilation can substantially reduce HAP. I put these numbers into context by comparison with systematic evidence on the impacts of ICS on HAP (Pope et al. 2021). In sum, the HAP reduction potentials I observe for *substantial* and *full* ventilation are comparable to what existing evidence suggests for the use of *improved* and *clean stoves* given typical levels of stove stacking, i.e., use of clean stoves alongside traditional stoves (Jeuland et al. 2012).

In my analysis of women’s pollution exposure, I find that the average exposure is highly harmful (136 µg/m³ PM_{2.5}), but substantially lower than kitchen pollution. Yet, in contrast with common beliefs and existing evidence (Smith et al. 2014, Shupler et al. 2020), I find a low median ratio of personal-to-kitchen pollution (0.36). This emphasizes the need to understand the drivers of heterogeneities in these ratios, and to adjust policy action accordingly. In line with this, I find that exposure is not significantly associated with kitchen ventilation. Plausible explanations for this relate to measurement error, kitchen separation from the main living space,

and survey effects. With respect to measurement, it is logistically more difficult to measure exposure for a moving target, i.e., here a person. In this vein, I may not be able to fully capture the manifold drivers of women's exposure, such as ambient air pollution. I furthermore look at a setting where most kitchens (89 percent) are separated from the main building, limiting exposures to cooking-related HAP to times of cooking. Alternatively, survey effects may induce women to reduce their exposure. Finally, I provide suggestive evidence that there is some selective, behavioral risk reduction by women who are involved in cooking in highly polluted kitchens, such as opening windows more when pollution is high.

Kitchen ventilation has only recently begun to attract attention within international frameworks aimed at reducing HAP. Since 2019, the Multi-Tier Framework for Measuring Access to Cooking Solutions (MTF) by the World Bank penalizes emissions less if there is high housing ventilation as compared to low ventilation.⁸⁶ In a similar vein, the recent Cooking Energy System (CES) by Energising Development (EnDev) assigns a major role to kitchen ventilation within a holistic cooking framework. However, consideration of housing ventilation has made only limited inroads into policy action and research, which largely regard stoves and fuels as factors isolated from the broader cooking environment.⁸⁷

Legitimately, it is the ambition of clean cooking policy to make access to clean cooking universal in the longer run, e.g., with liquified petroleum gas (LPG), ethanol, biogas, high efficiency gasifier, solar, or ultimately electric stoves. However, there is a very active debate on whether governments should exclusively promote fully *clean* technologies, or also *improved* biomass technologies that are adapted to local contexts and affordable. *Improved* stoves generate environmental, rather than health, benefits (Simon et al. 2014, Bensch et al. 2015, Pattanayak et al. 2016, Hanna et al. 2016, Sambandam et al. 2015, Grieshop et al. 2011). Housing ventilation is inferior to these technological solutions in that it directs emissions away from people instead of eliminating them (such as building sewers but not treating wastewater),

⁸⁶ The three variables considered when designing these thresholds are (i) air exchange rate, (ii) kitchen volume and (iii) duration of cooking. For details see ISO (2018) and <https://mtfenergyaccess.esmap.org/methodology/cooking>.

⁸⁷ Research commonly treats ventilation as a contextual or secondary influence on users' well-being. For instance, the WHO's "Global database of household air pollution measurements"⁸⁷ (WHO HAP database, publicly available at <https://www.who.int/airpollution/data/hap-measurements/en/>) lists 93 studies with HAP measurements in an indoor area published between 1968 and 2017. Only forty percent of papers appear to report building construction materials, building types, ventilation, or volume of the structure. For these 40 percent, it is unclear from the database, whether they consider ventilation in analyses as opposed to only providing them for contextual understanding.

and in that it does not provide highly relevant co-benefits for forests, climate, and women's time use.

However, given persistent challenges and slow, or even negative, progress towards meeting universal clean cooking, my findings are critical for designing and targeting transitory policies. They imply, first, that policy can target ventilation to reduce HAP in homes. This includes relatively low-cost action, such as raising awareness about the benefits of keeping doors and windows open, or simple improvements in housing ventilation via windows. Second, they suggest that targeting of cookstove policy should consider housing ventilation. On the one hand, fully *clean* stoves have plausibly higher pollution reduction potentials in households with *poorly* ventilated kitchens. On the other hand, low-cost *improved* stoves combined with, or targeted to households with, *highly* ventilated kitchens may be a cost-effective interim solution (for similar claims see Langbein et al. 2017 and Teune et al. 2020). Third, research on the impacts of cooking fuels or stoves systematically needs to control for housing ventilation. Fourth, my findings support the spirit of the CES in calling for a more holistic view of the cooking environment. Cooking in poor households in the global south is a multifaceted microcosmos in which technologies, fuels, housing, and cooking culture are inseparably linked.

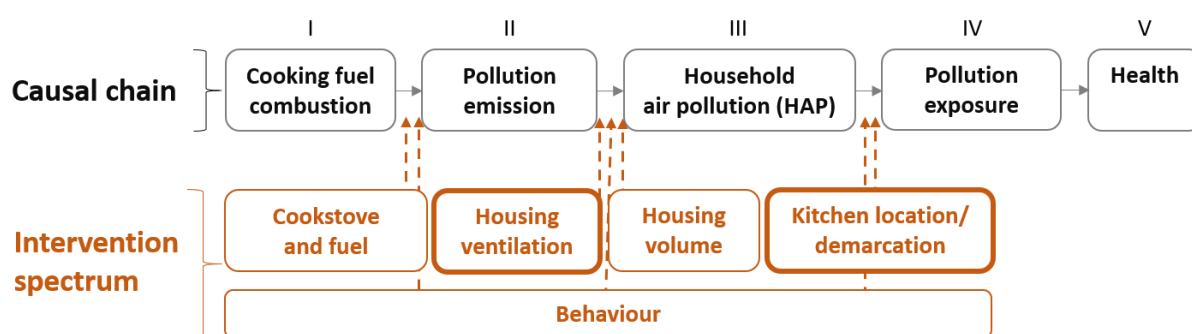
This chapter is structured as follows. Section 3.2 summarizes the underlying conceptual rationale, and Section 3.3 provides the systematic literature review, synthesizing study selection and results. Section 3.4 discusses the identification strategy, and Section 3.5 the HAP and kitchen measurements. Section 3.6 provides descriptive statistics for the field sample in Senegal, and Sections 3.7 and 3.8 present the associations of kitchen ventilation with kitchen pollution and with pollution exposures, respectively. Section 3.9 concludes.

3.2 Conceptual rationale

From a public health perspective, the ultimate objective of clean cooking interventions is a reduction of HAP-related health burdens. Figure 3.1 illustrates the causal chain linking combustion of fuels from traditional cooking to health outcomes and the spectrum of political intervention.

Traditional stoves combust solid fuels inefficiently. Pollution emissions refer to the particles emitted by a stove in the combustion process, such as fine particulates, carbon monoxide, nitrogen oxides, and volatile organic compounds. HAP is then the emission concentration per unit of (kitchen) area. Pollution exposure refers to the pollution a person is exposed to and hence inhales. Lastly, high exposures adversely affect health.

Figure 3.1: Stylized causal chain and intervention spectrum



This chain can be disrupted at any point, providing a spectrum for intervention (Figure 3.1 with chains numbered from I-V). Cookstove and fuel interventions aim to break or weaken the first link (I-II), by reducing the emissions emitted by a cooking device. Cooking behavior can affect several subsequent links, for example reducing emissions via correct stove use, use of dried (rather than wet) fuels, or reducing exposure via limiting kitchen contact time to the necessary. Conversely, behavior can also undo interventions, such as when cooks stack clean and dirty fuels or stoves.

The hypothesis advanced in this chapter is that HAP concentrations can also be altered by ventilated housing (disruption of link II-III). The effect is mechanical. Keeping emissions constant, pollution will be lower in a space with higher air ventilation and exchange, because particles move towards openings (Patel et al. 2017) and hence diffuse more to other spaces. While this is true for any room of a house, the relationship is most relevant in kitchens, where cooking-related pollution is plausibly highest. Accordingly, most studies focus on pollution in kitchens as opposed to living spaces or bedrooms (see Appendix Text extension 3A.1), as does my empirical analysis. The next section discusses this link, i.e., ventilation and household air pollution, systematically. It concentrates on field studies with actual HAP measurements. For evidence from secondary data, see for example Langbein et al. (2017).

In addition to ventilation, two further housing characteristics may affect HAP or pollution exposure. First, housing volume affects HAP directly (because emissions dilute more within a larger space; disruption of link II-III), and plausibly interacts with housing ventilation and other behavioral and stove technology choices. Few studies have looked at kitchen size (9 studies in Appendix Text extension 3A.1). My analysis of household data (Section 3.7) only shortly discusses volume, as the sample is too small for interaction analyses, and as ventilation is more easily modifiable via small housing or behavioral changes. Peoples' and policy's ability to change kitchen volume, by contrast, is bounded by housing space and existing kitchen

structures, and can therefore be more expensive. Second, kitchen location or demarcation from other living spaces can affect pollution exposure of cooking and non-cooking individuals in other rooms (disruption of link III-IV). Some prior studies consider kitchen location (seven studies in Appendix Text extension 3A.1), and I consider one location indicator in my empirical analysis of pollution exposures (Section 3.8).

Multiple factors can alter the suggested impact of housing ventilation on air pollution. Most importantly, effectiveness of ventilation is conditioned on the quality of ambient air. Studies from urban areas have indeed shown that ventilation can worsen indoor air when ambient air pollution or neighbors' emissions are high (Zhou et al. 2011, Patel et al. 2017, Mönkkönen et al. 2005, Shibata et al. 2014, Saksena et al. 2003). Furthermore, season and weather can impact air pollution directly, or indirectly via changes in ventilation behavior (Kulshreshtha and Khare 2011, Nayek and Padhy 2017). Ventilation behavior, e.g., effective use of windows, can as well be compromised for privacy or security concerns (Muindi et al. 2016, Lueker et al. 2020).

There is some evidence on other links in this causal chain, that I do not cover in my systematic review or micro-data analysis. First, a set of papers looks at the impacts of stove technologies and fuels on HAP or pollution exposure (I-III/IV), disrupting the link from cooking fuel combustion to pollution emissions (I-II) (see for example systematic reviews by Pope et al. 2021 and Jeuland et al. 2021). As cooking technologies are the most popular policy intervention for reducing HAP in low-income countries, I refer to this literature throughout the chapter. Second, there is a substantial literature suggesting a strong negative relationship between HAP from solid fuel combustion and various health outcomes in the global south (III-V) (for systematic reviews see Chafe et al. 2014, Ezzati et al. 2002, Dherani et al. 2008, Jeuland et al. 2021, Po et al. 2011, or Amegah et al. 2014). There is, however, evidence on a positive relationship between improved stoves and health outcomes, suggesting that a disruption of link I-II through the use of improved stoves can reduce the negative impact of fuel combustion on health (Mortimer et al. 2017, Romieu et al. 2009, Singh et al. 2012, Smith et al. 2011, Zaman et al. 2017). Ventilated cooking, i.e., disruption of link II-III, may be another possibility to reduce the negative impact of fuel combustion on health, but the literature on this relationship is scarce. A few studies suggest that better housing ventilation reduces incidence of acute lower respiratory infections among children across various countries (Rehfuess et al. 2009, Buchner and Rehfuess 2015, Langbein 2017), and reduces bronchitis in Bolivia and respiratory problems in Ghana (Albalak et al. 1999, Boadi and Kuitunen 2006). Bensch and Peters (2015) propose that increased outdoor cooking as a reaction to a new, portable stove may have improved self-

reported health in Senegal. Third, although not depicted in the causal chain above, the literature on housing and health is closely related. Housing can have physical and mental health consequences either via the quality of a house's internal facilities (e.g., water, sanitation, electricity, cooking and refrigeration) or due to the structure and permeability of housing materials (e.g., humidity, walls, roofs and floors) (Harris and Arku 2006, Bradley and Putnick 2012, Cattaneo et al. 2009, Galiani et al. 2017, Dedman et al. 2001). In line with the argument made in this chapter, the housing literature thereby identifies housing material as a potential mediator in this relationship between indoor air pollution and health.

3.3 Systematic Literature Review

3.3.1 Study selection

This section systematically reviews the literature on the relationship between housing ventilation and cooking-related air pollution in developing and emerging countries. To capture the full scope of the scattered evidence, I conduct the review across disciplines and regardless of study design, publication year and sample size. This review was pre-registered with Prospero.⁸⁸

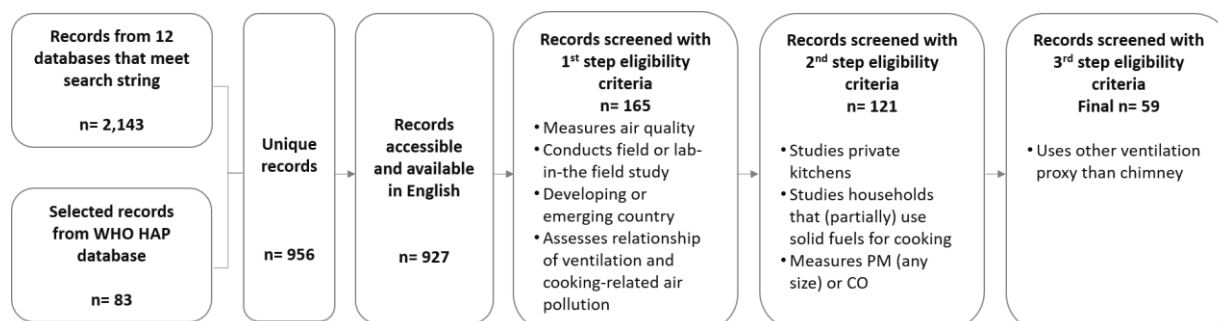
To identify relevant papers, I screened 13 databases together with two research assistants. First, we screened 12 databases⁸⁹ using a systematic search string that selected a record if its title, abstract or keywords included at least one search term in each of multiple categories. The categories relate to ventilation (e.g., *outdoor* or *window*), to pollutants (e.g., CO, PM), to air pollution (e.g., *exposure* or *emissions*), to pollution sources (e.g., *fire*, *charcoal* or *cookstove*), as well as to developing or emerging countries. See Appendix Table 3A.1 for the complete search string. The search yielded 2,143 records. Second, we manually identified 83 records from the WHO HAP database that study a setting with biomass cooking and elicit housing or ventilation information. Removal of duplicates (n=1,270) and studies that are not available in

⁸⁸ Prospero is the international prospective register of systematic reviews by the National Institute for Health Research (NIHR). I submitted the first version of the registry in October 2020, and it was made public in November 2020 under the registration ID CRD42020203920. All analyses done in this paper were pre-registered in the first version of the registry. In December 2020, I modified the registry to include the 2nd set of eligibility criteria that finetuned the record selection process further. I also made changes to the registry after recognizing that identified studies are largely observational and employ highly heterogenous, often incomplete, estimation and reporting practices. Most importantly, due to the fragmented methods apparent in the literature, I removed (i) the implementation of a meta-analysis of effect sizes, and (ii) the systematic assessment of risk of bias.

⁸⁹ Including Web of Science, PubMed, EMBase, and the following 9 databases via EBSCOhost: EconLit, Academic Search Premier, Business Source Premier, GreenFILE, MEDLINE, APA PsycArticles, APA PsycInfo, PSYNDEX Literature, CINAHL.

English, untraceable online, or inaccessible via multiple organizations and libraries (n=29), yielded a sample of 927 records (see Figure 3.2).

Figure 3.2: Study selection flow chart



One research assistant then screened the records' abstracts – and if necessary main texts – for three sets of eligibility criteria (Figure 3.2), which resulted in a final set of 59 records. In sum, this includes field studies with HAP measurements in low- or middle-income countries that relate housing ventilation to (PM or CO) pollutions or exposures in private (as opposed to commercial) households that rely on solid fuels for cooking. The included papers are listed in Appendix Table 3A.2. The research assistant carried out data extraction for all included studies using a comprehensive and pre-piloted data extraction form. Unclear records were reviewed and discussed by three reviewers.

3.3.2 Synthesis of results

In the Appendix (Text extension 3A.1), I describe the evidence from the set of chapters in detail, looking at its geographical coverage, publication year, and disciplines. Among others, I show that there is no consensus on how to approximate for ventilation, and that sample sizes are small in many studies.

In this section, I summarize the direction and statistical significance of the relationship between housing ventilation and air pollution as reported by the included studies. In this overview, I exclude studies that use theoretically unsound comparison groups (n=8 studies, 81 estimates)⁹⁰. Moreover, I cannot consider a few studies that provide insufficient information on the direction

⁹⁰ The excluded ventilation comparison groups do not proxy for theoretically worse or better ventilation, instead they compare for example mud walls vs. cement walls, or tile roofs vs. tin roofs. Moreover, some studies approximate for ventilation by season (winter vs. summer), village, or geography (lowland vs. mountainous); these are poor approximations that aggregate various factors which could theoretically affect ventilation both positively and negatively.

or significance of their results (three studies, 22 estimates). The final analytical sample thus consists of 48 studies with 262 distinct estimates.

Figure 3.3 illustrates the direction and statistical significance (for $p < 0.1$) of the association between improved housing ventilation and air pollution for the full sample of 262 estimates (Panel A), as well as for a restricted sample of 16 studies with a household sample size of at least 200 (Panel B). For both samples, a substantial share of estimates find that improved housing ventilation is associated with significantly lower pollution levels (24 percent and 45 percent). When restricting to studies with sample sizes larger than 100 or 300, these shares are roughly 35 percent. Appendix Table 3A.3 moreover provides the same statistics separated by pollutant and measurement area for different samples. The share of negative and significant associations varies between 17 and 100 percent, but sample sizes are partly small in these subgroup descriptive statistics.

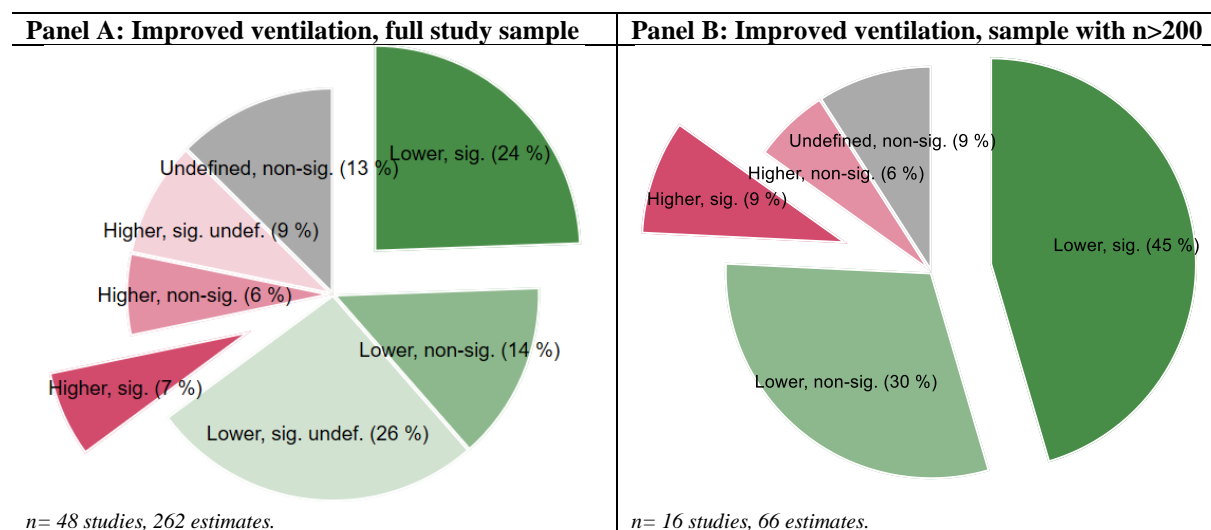
For context, I compare the results to those of a full-fledged meta-analysis by Pope et al. (2021)⁹¹ on the impacts of ICS – rather than ventilation – on HAP. Looking at 27 studies on *improved* solid fuel stoves (without chimneys), the authors' data suggests that 41 percent find significantly lower HAP. This share is within the ranges I find in my systematic review of the ventilation literature, depending on the sample size restriction I apply. This is an important finding, given the strong political focus on ICS only.

Interestingly, the same meta-analysis shows that an even higher fraction of studies (80 percent of 76 studies) finds that *improved* solid fuel stoves *with chimneys* reduce HAP. Conceptually, such technologies pair an improved stove with an extreme form of ventilation, i.e., chimneys, that redirects emissions directly at their source.

In sum, the overall evidence points towards a negative relationship between housing ventilation and kitchen pollution or pollution exposure. The review also shows that the general research question on the importance of ventilation for HAP and exposure has been identified as relevant by multiple disciplines. However, some of the existing studies should be interpreted with care, as the role of ventilation is often only a secondary research question, sample sizes are small, or comparison groups likely different in systematic ways. I intend to overcome these limitations in the following analysis.

⁹¹ Note that the results of this systematic review and the meta-analysis are not directly comparable.

Figure 3.3: Air pollution and improved housing ventilation, significance and direction of effect in the literature



Note: Results are aggregated across multiple pollutants (PM of different sizes, CO) and measurement areas (kitchen pollution, bedroom or living room pollution, pollution exposure). I report significance as reported in the studies. Here, a result qualifies as “significant” if $p < 0.1$. “Lower” refers to lower HAP, “higher” to higher HAP.

3.4 Identification strategy and sampling

To isolate the casual impact of ventilation on HAP, or more specifically kitchen pollution, and pollution exposure, one would ideally vary ventilation randomly. Such an experiment would however be logistically difficult to implement without considerable resources to modify housing structure as well as user buy-in. To the best of my knowledge, there is no data from such an experiment. As a second-best approach, I use my uniquely detailed data in a pooled panel data analysis to control for potential confounders and improve the goodness-of-fit of my model. Importantly, while the analysis controls for a rich set of controls, it does not necessarily imply causation.

There are at least three factors that may confound the estimated association between housing structure and pollution, namely wealth, poor health, and culture. Table 3.1 summarizes how the three confounders may impact both housing ventilation and pollution. If they impacted ventilation positively and pollution negatively, I would overestimate or even falsely identify a negative relationship between the two if not sufficiently controlled for.

First, to impede confounding via wealth, my multivariate analysis controls for a large set of wealth indicators⁹². Second, health could be endogenous, i.e., not only health may impact ventilation, but also vice versa, and controlling for it can hence introduce reverse causality into

⁹² This includes: the occupation and ethnicity of the main cooks, whether the head of household is a farmer, a wealth index that relies on 19 reported items, and two proxies for access to water and electricity infrastructure.

my estimates. I therefore exclude (objective and subjective) women’s health measures in my main analysis, but test whether my findings are robust to its inclusion in an alternative specification. Third, both housing structures and cooking practices in Senegal differ across ethnic groups, which – depending on the direction of effects – may either confound my estimation or simply add noise. To reduce the risk of potential confounding, I control for primary ethnicity and some aspects of cooking behavior⁹³, but acknowledge that behavior is a complex trait that is difficult to fully capture using quantitative indicators.

Table 3.1: Potential confounders and their direction of impact

Confounder	Positive impact on housing ventilation	Negative impact on pollution and pollution exposure
Wealth	↑ e.g., households afford larger kitchens/ obtain fans or windows.	↓ e.g., households purchase cleaner stoves/ buy cleaner or drier fuels/ cooks spend less time cooking due to higher opportunity costs.
Poor health	↑ Cooks are incentivized to apply better ventilation practices, e.g., keep doors open.	↓ Cooks are incentivized to reduce pollution and pollution exposure, e.g., using dried fuelwood, chopping fuelwood that burns more efficiently, avoiding use of plastics to light fires, leaving kitchen spaces during peak pollution events.
Cooking Culture	? Households build kitchens according to culture and tradition, e.g., use permeable materials.	? Cooks prepare food and fuel according to culture and tradition, e.g., duration of dish preparation, quantity of dishes and hot drinks, family size.

Moreover, I assess the robustness of results to specifications involving multiple alternative indicators, multiple specifications of the outcome, i.e., average and percentile pollution levels, and sub-sample analysis.

Given that my controls capture the above factors only imperfectly, I investigate the role of unobservables in my estimates using the Oster method (2019). I apply it to specifications where technically possibly, i.e., those that estimate one coefficient for ventilation only. The Oster method formalizes a well-known link, namely that smaller changes in coefficients paired with larger changes in R-squared after the inclusion of controls eases concerns about omitted variable bias.⁹⁴ To assess omitted variable bias, the method compares the values for the coefficient of interest and R-squared in a specification with and without controls to learn about coefficient behavior. It then suggests that the relationship between a coefficient of interest and

⁹³ This includes indicators from the following questions: “Do you regularly burn agricultural waste at home?” (Dummy for No); “What can you do to reduce burdens [of unclean cooking on your family’s health, water sources and air quality]?” (Dummy for naming at least one action); “In which situations do you escape the kitchen smoke?” (Dummy for naming at least one situation)

⁹⁴ Oster has become a well-established approach that extends work by Rosenbaum and Rubin (1983) on binary outcomes, and a similar conceptual approach by Imbens (2003).

unobservables can be estimated from its relationship with observables. The method requires to define a maximum R-squared, $R\text{-squared}_{\max}$, which Oster (2019) suggests setting to 1.3 $R\text{-squared}_{\text{observed}}$. This allows to estimate the ratio of selection on unobservables to selection on observables which would make the coefficient of interest equal to zero (delta). A delta higher than one signals that unobservables are more important than observables for the selection into ventilation. It is commonly interpreted as support for the model specification. Here, for ventilation to be unrelated to HAP, unobservables (i.e., unobserved cooking culture), would have to be more important for selection into ventilation than the full set of observed controls (e.g., wealth).

To test the association between kitchen ventilation and air pollution, I conduct OLS estimations with the following specification:

$$\log(Y_i) = \alpha + \beta_1 \text{Ventilation}_i + \mathbf{X}'_i \boldsymbol{\beta}_2 + \epsilon_i \quad (1),$$

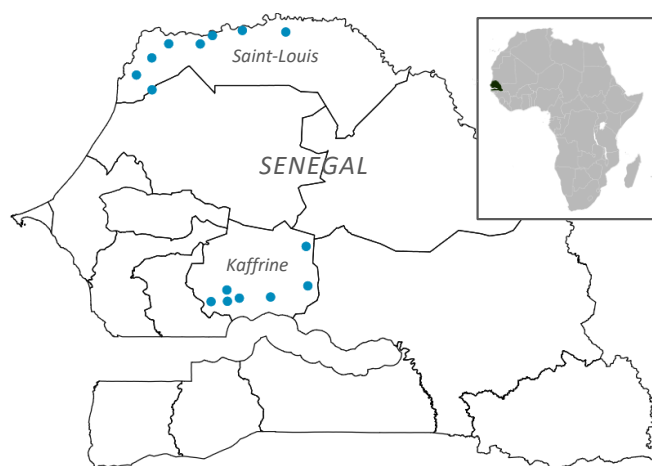
where $\log(Y_i)$ represents the logged outcome of interest for household i , i.e., mean 24-hour kitchen pollution ($\text{PM}_{2.5}$) in Section 3.7, and mean 24-hour women's pollution exposure in Section 3.8. I log-transform pollution as its bivariate relationship with ventilation is not linear and to reduce the influence of outliers. In a robustness test, I define the outcomes as pollution percentile, instead of average pollution.⁹⁵ *Ventilation* describes an indicator for household i 's kitchen ventilation, for which I test several alternative composite and single indicators. These are introduced in Section 3.5. $\mathbf{X}'_i \boldsymbol{\beta}_2$ represents a series of household and study participant characteristics, socio-economic household characteristics, cooking culture and behavior controls, and study and measurement characteristics. ϵ_i represents a household-specific error term. Standard errors are clustered at the household level to account for the pooled nature of the data.

Together with a field team and a team of researchers, I sampled communities from two regions in Senegal that have the typical Sahelian vegetation with scarce fuelwood. The inclusion criteria for communities were (i) total population between 600 and 1,600 to capture rural communities of typical size, (ii) location in a commune (4th administrative level) from which no other study community was sampled in order to increase geographical coverage, and (iii) absence of systematic firewood ICS promotion prior to our baseline survey to ensure low initial ICS penetration rates. Based on a household listing exercise, we randomly selected 35 households

⁹⁵ More concretely, I split the data into 20 percentiles covering the full 24-hour measurements. In splitting the data, I use intervals ranging between 0.5 and 10 percentiles. I use smaller intervals at higher pollution levels, as there is most variation in the data (see Figure 3D.1).

per community for participation in the original impact evaluation. Of these 35, we chose 16 to 17 households per community to participate in air pollution measurements via stratified random sampling. To select a sample that is balanced in terms of kitchen ventilation, the binary stratification variable was above or below median kitchen ventilation as generated via principal component analysis (PCA).⁹⁶ The sampling approach has the advantage of providing a sample that is representative for kitchen ventilation in the surveyed communities. We invited the households' primary cooks (henceforth study participants) above age 15 to participate in the interview; in case this individual was unavailable, a secondary cook participated instead.

Figure 3.4: Community location



Source: Own illustration (main Senegal map) and Shosholoz, licensed under CC BY-SA 3.0 (Africa map)

I use panel data from two household surveys in the 15 rural Senegalese communities (Figure 3.4) conducted in the dry season in early 2018 and early 2019. The data was also collected for a pre-registered⁹⁷ impact evaluation of two types of randomly assigned, improved woodfuel ICS, for which I control in the analysis below. To leverage the sample sizes from both data collection years, I pool the data, include a year dummy, and cluster at the household level. The sample used in this paper includes 220 household-year observations with kitchen pollution measurements, and 418 household-year observations with women's pollution exposure

⁹⁶ The PCA used seven variables following the intuition behind the CES: kitchen volume and kitchen openings, cooking location, the number of primary cooks, a dummy for stove stacking, daily cooking time, and main fuel type. The PC indicator used for stratification loads mostly on kitchen location and openings.

⁹⁷ We registered our impact evaluation with the Registry for International Development Impact Evaluations pre-registration (RIDIE) in September 2017 under Study ID RIDIE-STUDY-ID-59c9e0f49a591 and provided the Pre-Analysis Plan (PAP) in March 2019, prior to the second survey. The PAP prominently specifies heterogeneity analyses of the impact of our randomized ICS by an index that rates households as low, medium, or high in CES-related variables. It states that the final variable choice will include fuels and stoves, or behavioral parameters or kitchen structures (including ventilation and size), depending on each factor's relevance and variation in our sample. While the PAP hence does not specify the pooled analysis of this paper, it prominently documents our intention to assess the role of kitchen ventilation for air pollution and specifies the concrete variables I use here as main explanatory variables.

measurements. The samples are hence different, albeit largely overlapping (n=202, see Appendix Table 3B.1). Note that only three households attrite in year two due to absence of all household cooks.

3.5 Measurements

We collected granular and comprehensive data, including multiple variables referring to a 24-hour monitoring period, which 94 percent of participants categorized as a typical day. In sum, we measured three sets of variables, including (i) a large set of household characteristics, (ii) kitchen structures to approximate ventilation, (iii) kitchen pollution and women's pollution exposure measurements (PM_{2.5}).

More concretely, in terms of household characteristics (i), we first measured characteristics of the study participants and their households, information on cooking behavior during pollution measurements, and various study design and measurement-related factors that may impact measured pollution levels, as discussed below. Importantly, we directly measured cooking time using Stove Use Monitors (SUMs).⁹⁸

Second, we classified kitchen ventilation (ii). Our data collection closely followed EnDev's CES categories, which are based on the program's 15 years of experience across three continents in the cooking sector. The field team measured and classified roofs, walls, overall openness, and volume of the kitchens. I use the categorization to define the indicators with a range spanning from *no* to *poor*, to *substantial*, and to *full* ventilation, respectively (see Appendix Table 3B.2 for details). I use this categorization throughout this chapter. I rely on this data to construct two composite indicators, three single ventilation indicators, and one kitchen location indicator. Table 3.2 specifies the indicators and their generation.

My preferred indicators are the two composite indicators, i.e., quartile ventilation and principal component (PC) ventilation, as they combine various ventilation-related factors into a single informative variable, enhancing its suitability for regression analysis. The PC ventilation indicator is moreover continuous, allowing me to exploit variation along the entire ventilation distribution and hence increasing estimation precision. Moreover, it does not impose weights on the base variables, but instead leverages the correlation structure between them, which makes it less arbitrary. As to the non-composite indicators, the classifications of roofs and walls

⁹⁸ We measured cooking time objectively using Stove Use Monitors (SUMs) during the same 24-hour observation period. The SUM buttons were installed on one or two stoves per household, depending on the number of stoves regularly used by the households. Real-time temperature data was collected in intervals of 2.5 and 5 minutes, depending on the SUM model. The SUM data can then be used to objectively determine the number of cooking events, the time of use and stove stacking, i.e., use of multiple stoves.

themselves may serve as easy-to-collect, single indicators for ventilation, though they only partially explain overall ventilation. Moreover, a simple indicator for open air, that is provided by some larger datasets such as the Demographic and Health Surveys (DHS) data, may serve as ventilation approximation. I use these single indicators to test the robustness of the estimates.









Table 3.2: Definition of ventilation indicators

Indicator	Type	Variable generation
Quartile ventilation	Categorical	Sums up categorical roof and wall categories and splits the resulting score into quartiles.
Principal Component (PC) ventilation	Continuous	Defined as the coring coefficient from a Principal Component Analysis using roof, wall and general openness. The variable is recoded to a 0-1 range. The score explains 70 percent of variation in the PCA and loads similarly on all three components.
Kitchen wall	Categorical 1-4	Categorization in the field.
Kitchen roof	Categorical 1-4	Categorization in the field.
Open air	Categorical 0-1	Categorization in the field.
Location	Categorical 1-4	Categorization in the field.

Note: See Appendix Table 3B.2 for further details on categorizations in the field.

Lastly, I add a kitchen location indicator, i.e., with respect to the main building, as a potentially important driver of pollution exposures (Section 3.8). Figure 3.5 shows illustrative photos that demonstrate the range of kitchen structures in our survey population. It shows that there is considerable variability in housing ventilation even within two regions of the same country, underlying the need to consider ventilation heterogeneities in any discussion surrounding HAP in poor households from the global south.

Figure 3.5: Kitchen classification illustrated by field photographs

	No ventilation	Poor ventilation	Substantial ventilation	Full ventilation
Roof				
Wall				

Third, we measured PM_{2.5} kitchen pollution and women's PM_{2.5} pollution exposure during a 24-hour observation period (iii). PM_{2.5} is airborne fine particulate matter – with a diameter less than 2.5 micrometers – that originates from combustion processes. It is particularly damaging to human health, as it has a low likelihood of getting filtered by the upper respiratory tract due to its small size, and hence can penetrate deep into small body airways, lungs, and bloodstreams. We used two types of meters, namely Micro Personal Exposure Monitors (MicroPEMs) and Indoor Air Pollution (IAP) Meters developed by RTI International and Aprovecho, respectively. For kitchen pollution measurement, we installed a fixed meter at an approximate 1-meter vertical and horizontal distance from the households' main stoves. For measurement of pollution exposure, women agreed to wear the lightweight and quiet MicroPEMs at chest level to measure the fine particles they effectively inhale (see Appendix Figure 3B.1 for photographs).

The MicroPEM measures 24-hour average concentration, i.e., the PM_{2.5} mass that accumulates on the MicroPEMs' internal filters, controlling for the exact time and intervals of sampling.⁹⁹ This 24-hour average is the main outcome in my analysis. Additionally, both the MicroPEM and IAP meters provide real-time pollution data, by registering PM_{2.5} inflow in 30-second intervals via a light scattering particle detector built into the devices. I order the real-time pollution measurements from most polluting to least polluting. I thereby generate percentile data ranging from the 0.5th to the 99.5th percentile of 24-hour pollution. Note that I have this data from a subset of 140 (out of 216) kitchen pollution data points, and 344 (out of 436) pollution exposure measurements only. The reason for this missing data is problems with our field computers. Importantly, the data loss occurred after measurement and is unrelated to the households or measurements, i.e., at random. Moreover, I rely on these data for a robustness test only.

3.6 Summary statistics

3.6.1 Explanatory factors

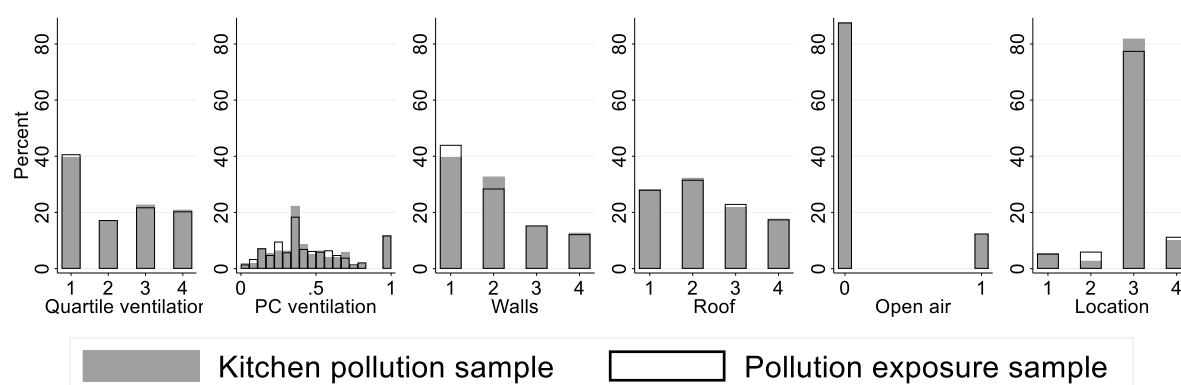
This section summarizes descriptive statistics of all explanatory and control variables used in my analysis. Appendix Table 3C.1 describes all control variables separated by subsamples with kitchen pollution and pollution exposure measurements. In line with expectations from the stratified randomization of measurements, the two sub-samples are very similar. The survey

⁹⁹ To calculate the average 24-hour kitchen pollution measurements from IAP meters, I use the average real-time data. The MicroPEM, by contrast, provides a direct measure for this outcome.

participants were on average 32 years old, and almost 60 percent were principally homemakers. They live in households with approximately 12 members, and spend on average 5.5 hours cooking per day, mostly (80 percent) using a traditional or basic metal stove. There are on average 1.4 primary cooks per household, who take turns. Seventy-three percent of study participants identify as primary cook, while 13 percent identify as secondary cook. Households used a stove that was located next to our meter during roughly 90 percent of all cooking events. Women wore the MicroPEM for pollution exposure measurement on average during 70 percent of daytime (already assuming eight hours of sleep), as measured by the MicroPEM's built-in accelerometer. I control for this in the analysis.

Turning to kitchen ventilation, Figure 3.6 shows the distribution of households across ventilation indicators. It shows, firstly, that only a small share of households (12 percent) cooks fully open air. Second, there is high variation in kitchen structures. Third, most kitchens are located separately from the main building. Finally, the two sub-samples with kitchen pollution and pollution exposure measurements are very similar with regards to their ventilation categorization because of our selection via stratified randomization. In line with their common variable base, the ventilation indicators have a high and significant monotonic dependence ranging between $r = 0.47$ and $r = 0.83$, and, in line with expectation, a lower dependence with the kitchen location indicator ranging between $r = 0.36$ and $r = 0.54$ (see Appendix Table 3C.2).

Figure 3.6: Distribution of households across ventilation indicators



Note: For categorical ventilation variables: 1= No ventilation, 2= Poor ventilation, 3= Substantial ventilation, 4= full ventilation (see Appendix Table 3B.2 for details). For kitchen location: 1= Inside main building, 2=Attached to main building, 3=separated from main building, 4= Open air.

3.6.2 Kitchen air pollution and pollution exposures

This section describes $PM_{2.5}$ kitchen pollution in 202 kitchens and pollution exposures of 418 women.

Table 3.3 shows the results from 24-hour air pollution measurements, and Figure 3.7 plots their cumulative distribution. They demonstrate, firstly, that kitchen pollution surpasses the WHO standards by a great deal, as does pollution exposure (see red lines for WHO targets). For example, WHO's least demanding, IT 3 is met by only 13 percent for kitchen pollution and 26 percent for pollution exposure, a threshold which, if exceeded, is associated with an estimated five percent increase in short-term mortality (WHO, 2006). Nearly no household meets the final WHO target of 25 $\mu\text{g}/\text{m}^3$ daily averages, neither for kitchen pollution nor for pollution exposures. Kitchen pollution also surpasses HAP in the world's most polluted mega-cities (Krzyzanowski, et al., 2014). This is an important finding that underlines the need for prompt solutions to HAP in this and similar contexts.

Second, kitchen pollution is much higher than pollution exposures, namely 312 and 110 $\mu\text{g}/\text{m}^3$ at the median, respectively (see different x-axis scales in Figure 3.7). Third, there is very high variation in both kitchen pollution and exposure across households. Finally, purely visually, open air cooking households have substantially lower kitchen pollution than (semi-) indoor cooking households, yet the corresponding study participants appear to experience only slightly lower pollution exposures. My analysis will look at these patterns more closely.

Table 3.3: Summary statistics of kitchen pollution and pollution exposure (PM_{2.5})

	Kitchen pollution				Pollution exposure			
	Mean	SD	Median	N	Mean	SD	Median	N
PM _{2.5} : mean	474	455	312	220	136	107	110	418
PM _{2.5} : 95 pctl.	1839	2204	780	140	379	556	234	344
PM _{2.5} : 25 pctl.	30	21	25	140	33	19	29	344

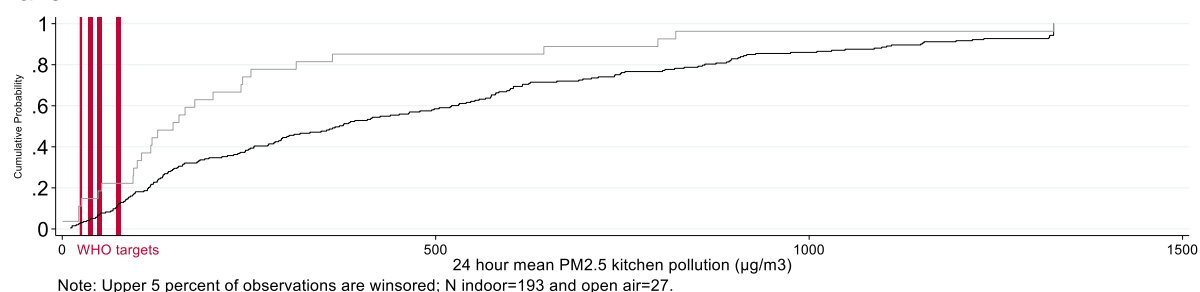
Note: pctl=percentile. The percentile values state that during 95 (25) percent of the day or 22.8 (6) hours, pollution is below that value. SD= standard error.

An exact dose-response relationship for PM_{2.5} pollution and health impacts is unknown, but evidence suggests that the function differs by disease, is in many cases nonlinear, and that only very low pollution levels bring substantial health improvements (WHO 2008, Ezzati and Kammen 2002, Burnett et al. 2014). At the same time, it is often assumed that some health response, in particular in terms of acute symptoms like coughing, may depend on peak rather than on average pollution. To identify variation in pollution over a day, I order the real-time pollution measurements (both for kitchen pollution and pollution exposure) from most polluting to least polluting. I then split them into percentile pollution values ranging from the 0.5th to the 99.5th percentile of 24-hour pollution. The interpretation of the 99th percentile value is, for

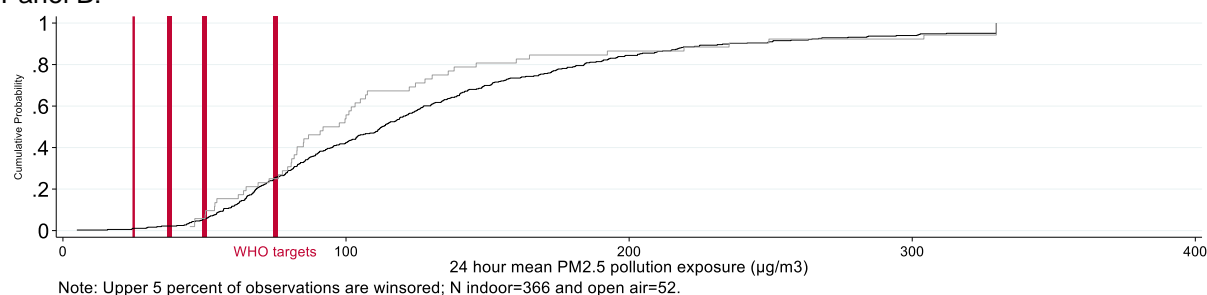
example, that for 99 percent of a day, i.e., around 23.8 hours¹⁰⁰, exposures are below that value.

Figure 3.7: Cumulative distribution of PM_{2.5} kitchen pollution (Panel A) and pollution exposure (Panel B), by outdoor versus indoor cooking

Panel A:



Panel B:



— Indoor — Open air

Note: The scale of the x-axes differs. Red lines indicate the WHO target and the interim targets 1, 2, and 3.

Table 3.3 shows the 25th and 95th percentiles (see Appendix Figure 3D.1 for all percentile averages). The 25th percentile is commonly understood as background pollution experienced during times without cooking. Even this value surpasses the WHO target value slightly, either suggesting that pollution remains high in closed structures or that secondary or ambient pollution sources contaminate the indoor environment. Note that the survey areas are generally shielded from traffic- and industry-related air pollution, but experience storms that can carry Saharan dust.¹⁰¹ Importantly, the 95th percentile reveals extremely elevated peak pollution.

3.7 Ventilation and kitchen pollution

This section quantifies the relationship between kitchen ventilation and kitchen pollution, and shortly looks at the role of kitchen volume and covariates. It also discusses the effect sizes in relation to international targets and findings from ICS interventions, assuming the identified

¹⁰⁰ To calculate the hours that correspond to a certain percentile, simply calculate: (percentile*24)/100

¹⁰¹ Our surveys took place in February and March. Generally, storms are, however, strongest in the rainy season from June to September, which can bring rain and thunderstorms.

effect can be interpreted causally. Lastly, it tests robustness of the findings using multiple approaches.

3.7.1 Relationship

Table 3.4 regresses average kitchen pollution on the two composite ventilation indicators, using a specification controlling only for year and community, and a specification controlling for the full set of control variables outlined in Appendix Table 3C.1.¹⁰² The coefficients in the log-linear model give the percentage change in average kitchen pollution when switching from *unventilated* kitchens to *poorly*, *substantially*, and *fully* ventilated kitchens.

Table 3.4: Ventilation and kitchen pollution (PM2.5)

	(1) PM b/se	(2) PM b/se	(3) PM b/se	(4) PM b/se
Quartile ventilation: poor	-0.31 (0.21)	-0.37* (0.19)		
Quartile ventilation: substantial	-0.48* (0.24)	-0.71*** (0.22)		
Quartile ventilation: full	-1.13*** (0.28)	-1.31*** (0.27)		
PC ventilation			-1.46*** (0.41)	-1.72*** (0.38)
Community and year	Yes	Yes	Yes	Yes
Measurement	No	Yes	No	Yes
Cook and household	No	Yes	No	Yes
Cooking behavior	No	Yes	No	Yes
N	220	211	220	211
Mean(Y) ref cat.	640.5	654.8	.	.
R-squared	0.211	0.463	0.195	0.446
delta				8.70

Note: ***, **, * denote statistical significance at the 1, 5 and 10% level respectively. The dependent variable is log of 24-hour average PM_{2.5} exposure. Standard errors are clustered at the household level and displayed in parentheses. The reference category of all variables of interest is their lowest category, i.e., most closed/smallest kitchen.

Moreover, Figure 3.8 graphically displays these effect sizes of all composite and single indicators as percentage changes using the full set of controls and adjusting for the outcome in logarithms¹⁰³. Both show my main finding clearly: fully, substantially, and depending on the specification and indicator also poorly ventilated kitchens have systematically and substantially less kitchen pollution than unventilated ones. This holds true across indicators.

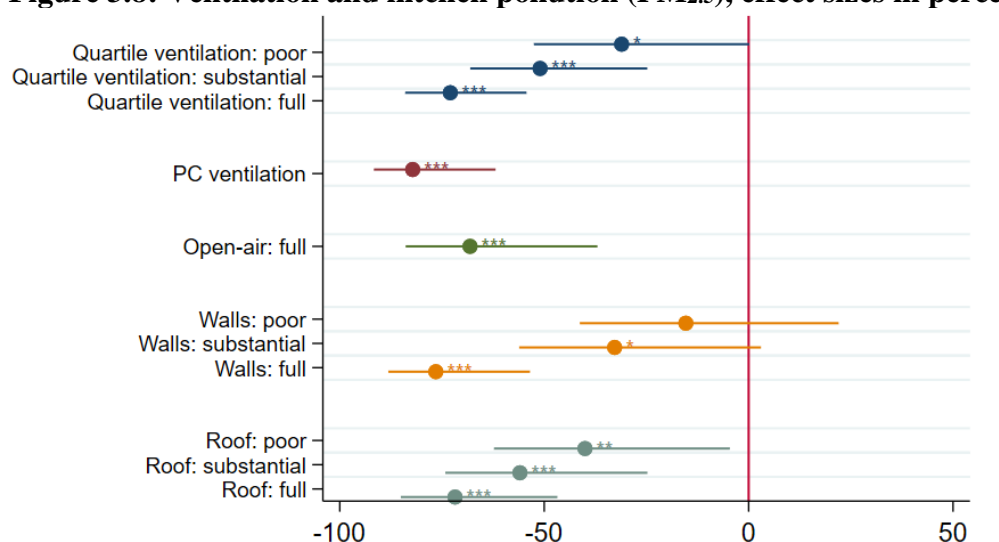
Lastly, for better overview of the effect size ranges, Table 3.5 lists the logarithm-adjusted effect sizes shown in Figure 3.8. They are not directly comparable, as they have different scales. Panel

¹⁰² For a stepwise introduction of control variable sets and results for single ventilation indicators, see Appendix Table 3D.2 and Table 3D.3.

¹⁰³ For large coefficients, the effect size becomes imprecise and needs to be transformed to adjust for the outcome in logarithms.

C reports on categorical indicators and gives the percentage change in kitchen pollution when switching from an *unventilated* kitchen (reference category), to a *poorly* ventilated, to a *substantially* ventilated and to a *fully* ventilated kitchen. Panel B shows the effect size given by the open air indicator, i.e., for switching from any inside cooking to open air cooking. Lastly, Panel C gives the change associated with switching from the lowest ventilation percentile (very closed kitchen) to the 33rd, 66th and 100th percentiles, as suggested by the PC ventilation indicator. Switching from *no* to *fully* ventilated kitchens is associated with a reduction of kitchen pollution between 67 and 82 percent, depending on the indicator I apply. The effect size of switching from *no* to *poor* ventilation varies between 15 and 40 percent, and from *no* to *substantial* ventilation between 33 and 56 percent.

Figure 3.8: Ventilation and kitchen pollution (PM_{2.5}), effect sizes in percent



Note: The coefficient plot displays the estimates of each ventilation indicator, using the specification with the full set of control variables. It indicates the estimates and the 95th confidence intervals (CI). Indicators whose CI intersect with the zero line (i.e., the reference line referring to unventilated kitchens) are not statistically significant. Coefficients are transformed with the formula $(\exp(\text{coef})-1)*100$ to account for the logged outcome and show percentage changes. $N=211$ in all estimations.

I show Table 3.4 with covariate coefficients in Appendix Table 3D.1 and Table 3D.2. Most importantly, the tables show that pollution levels were consistently and significantly lower when measured with an IAP meter as opposed to a MicroPEM¹⁰⁴, and when the dirtiest stove close to the meter is an LPG stove. They are also significantly lower when study participants are illiterate, cook for less people, or report to smell neighbors' smoke less than weekly. The latter may suggest diffusion of secondary pollution into the households' kitchens. The improved

¹⁰⁴ As outlined above, my main analysis uses data from two different measurement techniques. To measure PM_{2.5} concentrations, the MicroPEM used a filter (collecting gravimetric data) whereas the IAP meter used a light-scattering nephelometer (collecting real-time data). The MicroPEM filters may capture smaller particles than the sensor. The difference should be in levels and hence not bias my estimates.

and advanced biomass stoves assigned randomly to women as part of our main experiment do not significantly affect air pollution.

Table 3.5: Effect sizes associated with change in ventilation, by ventilation indicator and in percent

Panel A:	Poor ventilation	Substantial ventilation	Full ventilation
Quartile ventilation	-31.1	-51.0	-73.0
Wall	-15.4	-32.8	-76.5
Roof	-40.0	-55.9	-71.8
Panel B	Open air		
Open air	-67.4		
Panel C	33rd ventilation percentile	66th ventilation percentile	100th ventilation percentile
PC ventilation	-27.1	-54.2	-82.2

Note: Effect sizes are transformed ($\exp(\text{coeff}/CI)-1$) to account for the log-transformed outcome. For the (upper) categorical variables, it gives the percentage change in kitchen pollution when switching from an unventilated kitchen (reference category), to a poorly ventilated, to a substantially ventilated, and to a fully ventilated kitchen. For the open air indicator, it shows the percentage change associated with switching from any indoor to open air cooking. Lastly, for the PC ventilation indicator, it shows the percentage change associated with switching from lowest ventilation percentile to the 33rd, 66th and 100th percentile.

In these tables, I also explore the role of kitchen volume for my analysis. Volume may be an important determinant of kitchen pollution, either directly or in interaction with kitchen ventilation. Controlling for volume adds some explanatory power to the model, and some of the association between ventilation and pollution migrates to volume, but the association itself is not significant (Appendix Table 3D.1). In these regressions, volume is coded categorically to allow for estimations with the full sample, such that open air cooking – where volume measurement is pointless – can then be categorized as the highest category (4).¹⁰⁵ Moreover, one would expect that the role of volume for kitchen pollution increases as kitchens become less ventilated. Interacting volume and ventilation tentatively confirms such a relationship, but the results are noisy, and the sample size insufficiently powered to allow for clear interpretation. I accordingly do not report or discuss this further. In sum, these observations suggest that volume may play a minor role in kitchen pollution, and that size may be more important in less ventilated kitchens.

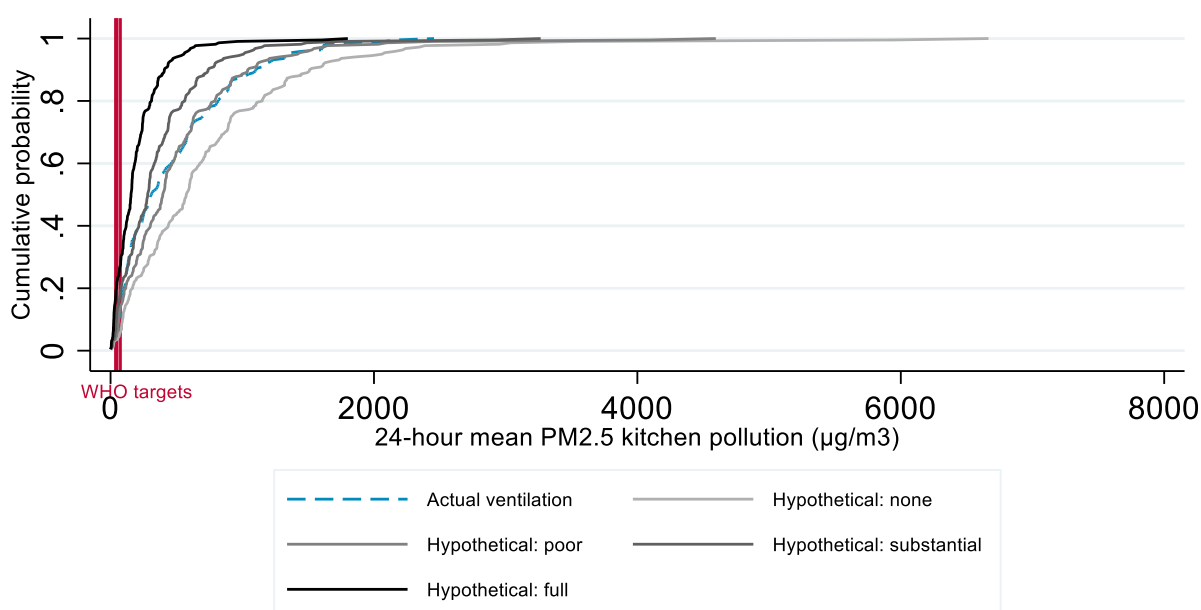
¹⁰⁵ Alternatively, to benefit from the rich continuous volume variable and to reduce the number of regressors, Appendix Table 3D.3 excludes open air cooking households and looks at the association between continuous volume and air pollution. It is only marginally significant, not robust, and, again, the effect migrates to ventilation when the latter is included.

3.7.2 Contextualization

To put the pollution reduction potentials into context, I now compare them to the evidence on *improved* and *clean stoves*, acknowledging that the studies are not directly comparable. A meta-analysis by Pope et al. (2017) finds from 34 studies that, on average, *improved* biomass stoves without a chimney, those with a chimney, and advanced biomass combustion stoves alter PM kitchen pollution by 52, 73, and 45 percent, respectively. These effect sizes correspond roughly to switching from *no* kitchen ventilation to *substantial* or *full* ventilation in my sample.

Regarding *clean* stoves, I make two comparisons. First, the same meta-analysis (Pope et al. 2021) finds from 15 studies that PM kitchen pollution decreases by 86 to 93 percent. The effect sizes I find for *fully* ventilated kitchens are only slightly lower, depending on the indicator we look at. Second, when discussing *clean* stoves, it is important to consider that poor households often use them alongside traditional stoves for only 30 to 50 percent of their cooking activities (Jeuland et al. 2012), a well-known phenomenon called stove stacking. Stove stacking reduces the effectiveness of *clean* stoves. My effect sizes for *substantial* and *full* ventilation are equivalent to doing between 67 and 82 percent and 33 to 56 percent of cooking on a fully *clean* stove with zero emissions, keeping everything else constant. This in turn implies that *substantial* ventilation has a similar average effect, and *full* ventilation a higher one, on reducing pollution than do perfectly *clean* stoves given typical levels of stacking.

Figure 3.9: Cumulative distribution of actual PM_{2.5} and hypothetical kitchen pollution assuming distinct kitchen ventilation conditions



Note: The graph uses effect sizes of the quantile ventilation indicator using the full set of controls.

To contextualize the reduction potentials of ventilation further, I now estimate households' hypothetical kitchen pollution if they all had *un-*, *poorly*, *substantially*, or *fully* ventilated kitchens. I rely on coefficients from estimations with the quartile indicator and the full set of controls (Table 3.4, Specification 2), and implicitly assume that the observed relationship is causal. Figure 3.9 compares the hypothetical kitchen pollution to households' actual pollution. It shows a stark shift in pollution, that – if all households had *fully* ventilated kitchens – corresponds to a reduction in median pollution from 312 to 156 $\mu\text{g}/\text{m}^3$. Despite these large reductions, average levels remain high. For example, if all households had *full* ventilation, the share that meets the least-demanding, interim-target of 75 $\mu\text{g}/\text{m}^3$ would increase from 13 to 27 percent. If all households cooked in *unventilated* kitchens, by contrast, the share decreases to six percent of households.

3.7.3 Robustness

While I cannot claim that the relationship between ventilation and kitchen pollution is causal, my analysis ruled out the most obvious alternative interpretation of the observed correlation. I discuss the four main omitted factors that may confound my results in Section 3.4. For most of them, I include various controls. However, as in any such analysis, the controls are likely imperfect proxies for the factors they are meant to measure. I therefore now discuss the robustness of the observed, significant, and large relationship between kitchen ventilation and kitchen pollution.

The relationship is qualitatively robust across indicators and specifications. The R^2 across indicators suggests that they explain roughly 20 percent of the variance in kitchen air pollution (only controlling for variance related to year and community). This is considerable, given the excessively high kitchen pollution in my sample. The R^2 increases further when including other control variables, such that the last and preferred specification explains at least 45 percent of variance across indicators.

My main analysis looked at average 24-hour pollution. As shown in Section 3.6.2., these averages exhibit a great deal of variation, ranging from simple background pollution at night to peak moments during high-intensity cooking. In a robustness check, I regress the $\text{PM}_{2.5}$ percentile data on the composite indicators and find that ventilation is statistically significantly associated with moments of high pollution, but not with medium and low pollution levels (Figure 3D.2 in Appendix). This is in line with expectations and raises confidence in my results.

Given the large R^2 , consistently robust effects, and the rich set of control variables, I am confident that the large observed association between ventilation and kitchen pollution signals a robust effect. To further investigate the role of unobservables in my estimations, I report Oster's delta for the two ventilation indicators, for which the Oster method can be calculated technically, i.e., the PC ventilation indicator and the open air indicator, in Appendix Table 3D.1 and Table 3D.2. The delta test statistic helps to verify whether the significance of an effect is robust, but not whether its effect size is precise. A delta larger than one is commonly interpreted as support for the model specification. I find that the delta both for PC ventilation and open air are extremely high, suggesting that unobservables in my model would need to be 9 and 17 times more important, respectively, than what my model observes to make the ventilation coefficient become zero. This suggests that the role of unobservables in my estimations is minor, again raising confidence in the results.

My analysis so-far excluded controls related to the participants' health, as it is endogenous to kitchen air pollution. In a separate estimation, I include a subjective indicator (cook reports having red eyes at least sometimes) and an objective indicator (has normal blood pressure), to see whether my results hold. Effect sizes of some ventilation indicators increase slightly but are otherwise highly robust to my prior findings. Self-reported experience of red eyes is significantly related to kitchen pollution, likely reflecting reverse causality (see Appendix Table 3D.4).

Lastly, to test whether the observed association is driven by households with *open air* kitchens, I run the same estimations with a reduced sample that excludes them (eight percent in the kitchen pollution sub-sample). Appendix Table 3D.5 shows that the quartile and PC ventilation indicators decrease slightly in size, but remain large and significant, suggesting that the effect I identify is not only driven by households cooking outdoors.

3.8 Ventilation and women's pollution exposures

From a public health perspective, the final objective of clean cooking policies is to reduce pollution exposures and thereby adverse health effects. Measurement of kitchen pollution is often considered a less costly, second-best alternative to measuring pollution exposure, as it is assumed to correlate with individuals' exposure and it is less demanding technically and financially, and on study participants. At the same time, reducing kitchen pollution can be a goal in and of itself, if the aim is to create indoor environments that are safe, independent of the time people spend in these environments. Generally, approximating exposure by kitchen

pollution is most appropriate for individuals who spend much time in the monitored area or individuals that face similar concentrations in and outside the monitored area (WHO 2008).

However, the median ratio of personal-to-kitchen PM_{2.5} pollution is only 0.37 in my sub-sample of households that participated in both measurements (n=202).¹⁰⁶ This is lower than in most previous studies, which find median ratios of 0.74 in India (Smith et al. 2014), and ratios slightly smaller than 0.5 in Bangladesh, Tanzania, and Zimbabwe but higher than 0.9 in China, India, Chile and Columbia (Shupler et al. 2020).

There are at least four potential explanations for the low ratios in my study context. First, I likely do not observe all drivers of pollution exposure. Unobserved drivers of pollution exposures in my model are plausible, as exposures depend on a set of hard-to-measure (behavioral) factors, such as the pollution the women face during non-cooking activities, and the secondary and background exposures in their households and communities. This is enhanced by the fact that women wore the meter on average around 70 percent of daytime, leaving some activities unobserved. In line with this argument and despite the doubled sample size, a multivariate analysis of women's exposure to pollution (see Table 3E.2 and Table 3E.3) explains a much lower share of its variance ($R^2=0.26$ in Table 3E.2, Specification 5) than the analysis of kitchen pollution using the same model specification ($R^2=0.46$ in Table 3.4, Specification 2).

Second, survey effects may be at place, where women are sensitized to avoid smoke by our interviews and device carriage. However, somewhat similar survey effects should be in place also in other surveys, that find higher ratios.

Third, most kitchens in my sample (89 percent) are fully separated from the main living space, reducing pollution of other living spaces. The location coefficients in Figure 3.10 do not support this interpretation, but high confidence intervals call for caution with interpretations.¹⁰⁷

Fourth, women may selectively respond to pollution with behavioral smoke avoidance, i.e., avoid pollution by leaving smoky kitchens more, or open doors in polluted places more. The more they do so, the less important will kitchen pollution be for pollution exposures. A story of selective smoke avoidance could, for example, be that avoidance behavior delivers benefits in *poorly* ventilated places, cancelling out the effect of *poor* ventilation on exposures. A more

¹⁰⁶ The ratio is somewhat higher for peak pollution, e.g., at the 90th percentile or the 2.4 most polluted hours, amounting to a median ration of 0.48.

¹⁰⁷ Note that kitchen location remains insignificant also when including a ventilation indicator in the model (except for open air cooking) (not shown).

complex, non-linear relationship could be that behavior cancels out ventilation in *substantially* ventilated places, but not in *fully* ventilated places where risky behavior does not threaten the realization of some benefits.

I cannot rigorously test such behavioral responses but have three indications that they may be at play. First, against intuition but in line with selective responses, median personal-to-kitchen ratio increases with better ventilated kitchens.¹⁰⁸ This is also in line with data from Pope et al. (2021) who find higher ratios for households with clean stoves (around 0.7-0.8) than with traditional stoves (around 0.5). Second, I assess the relationship between two proxies for behavioral smoke avoidance and ventilation using the full set of control variables (Appendix Table 3E.1). I observe a significant and positive relationship between better ventilated kitchens and never opening windows (but none for reporting to avoid smoke). While this may lend some tentative support to the theory that women respond selectively to high air pollution, it may also (partly) reflect that there are less windows to be opened in a more open kitchen. Third, Figure 3.10 shows that three of the indicators (kitchen location, quartile ventilation, and wall ventilation) are non-linearly and significantly related to pollution exposure, which either reflects large confidence intervals, or selective smoke avoidance behavior.¹⁰⁹ Similarly, women may respond differently depending on their baseline health. Introducing (endogenous) health proxies to the estimation Table 3E.4), does not confirm this. Instead, significance is reduced further, and the selected health covariates are not significantly related to pollution exposures to PM_{2.5}.

Figure 3.10 furthermore confirms that the low ratios of personal-to-kitchen pollution negate any impact of kitchen ventilation on women's pollution exposure. Except for the non-linear significances discussed above, overall, effect sizes are small, significance is marginal at best and not robust to different specifications and indicators.¹¹⁰ Looking at the covariates in Appendix Table 3E.2, I see that several factors are significantly associated with higher pollution exposures. This includes most prominently a longer MicroPEM wearing time (but coefficients

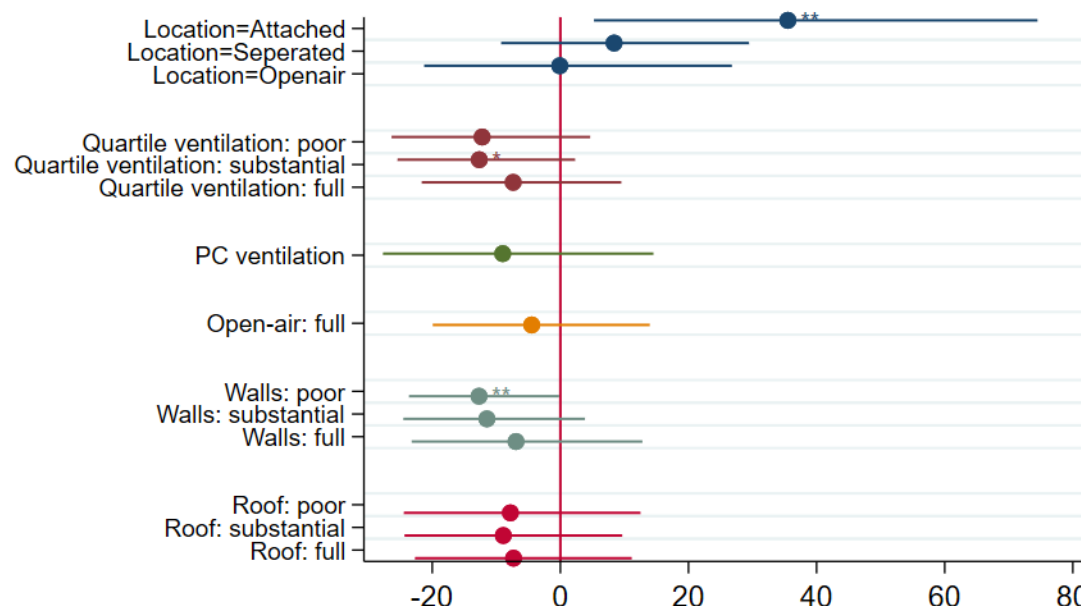
¹⁰⁸ More concretely, households with increasingly open kitchens (i.e., quartile ventilation from 1 to 4) have median ratios of 0.24, 0.35, 0.46, and 0.65, respectively.

¹⁰⁹ Figure 3.10 shows the transformed coefficients from a multivariate regression using the full set of control variables. Appendix Table 3E.1 and Table 3E.2 show the regression output. The framework is the same as for kitchen pollution but includes three additional factors that are relevant to exposure (the number of persons cooking during the measurement period, whether participants were secondary or main cooks during measurement, or neither, and the share of daytime wearing of the MicroPEM) and excludes two factors that are not (meter type and share of cooking events next to monitored stove).

¹¹⁰ I make the same observation when regressing percentile pollution exposure, i.e., times of particular low and high pollution, on ventilation (not shown). I furthermore confirm this observation for the reduced sample of primary cooks only (not shown).

are close to zero), and whether participants were the households' primary cooks during measurement. The treatment stoves assigned randomly to households as part of the main experiment underlying this study again do not observably impact pollution exposures.

Figure 3.10: Ventilation, kitchen location, and pollution exposure (PM_{2.5}), effect size in percent



*Note: The coefficient plot displays the estimates of each ventilation indicator, using the specification with the full set of control variables. It indicates the estimates and the 95th confidence interval (CI). Indicators whose CI intersect with the zero line (i.e., the reference line referring to unventilated kitchens) are not statistically significant. Coefficients and CI are transformed $(\exp(\text{coef./CI})-1)*100$ to account for the logged outcome and show percentage changes; $n=413$ for the kitchen location estimation, and $n=414$ for all other estimations.*

3.9 Conclusion

Current trends and projections suggest that a considerable share of the world's rural populations will continue to cook with dirty fuels and stoves in the years to come (IEA et al., 2020), resulting in tremendous health and environmental hazards, disproportionately burdening the poorest of the poor. Interim solutions are required on the challenging path towards universal clean cooking. This chapter has combined evidence from a systematic literature review with micro evidence from Senegalese panel data to suggest ventilated housing as an interim policy instrument to complement current clean cooking programs.

I have provided five main findings. First, I have quantified highly elevated kitchen pollution and pollution exposures among rural, Senegalese households, that exceed WHO safe levels by a lot. Second, my analysis has overcome some limitations of the existing evidence and has found that both gradually and much better ventilated kitchens are associated with less HAP in kitchens. The associations are large, highly significant, and withstand multiple robustness tests.

Third, comparisons of my findings with those of Pope et al. (2021) suggest that *substantial* housing ventilation in my Senegalese sample has similar potentials to reduce kitchen pollution as being equipped with a non-chimney, *improved* stove. Consideration of typical levels of clean stove stacking (30-50 percent in Jeuland et al. 2012) suggest that *substantial* ventilation is even associated with HAP reductions comparable to more advanced, *clean* stove interventions. Switching to a fully open kitchen could have even higher potentials when considering such stove stacking levels.

Fourth, I do not observe a statistically significant relationship between kitchen ventilation and women's pollution exposure to PM_{2.5}. I also find a median ratio of personal-to-kitchen pollution (0.36) that is lower than in most previous studies (Smith et al. 2014, Shupler et al. 2020). This is an important finding, as it may suggest that indoor pollution is not as important as believed for personal exposures, and hence the focus of international policy is misguided. However, I caution such conclusions as personal-to-kitchen pollution ratios are plausibly highly context dependent (reflected in high heterogeneity in ratios across studies), and as one can also argue that safe indoor environments should be a goal in and of themselves. I have discussed at least four potential reasons for the absence of an effect in the context studied here: omitted drivers of exposure in my model and measurement during 70 percent of daytime only, survey effects, demarcation of the kitchen from the main living space, and selective smoke avoidance by women.

Fifth, my systematic review of 59 academic papers across disciplines has shown that the evidence is scattered, yet in the aggregate, points to a significant and negative association between housing ventilation and HAP or pollution exposure. Indeed, the share of negative and significant associations is similar to what is found in a recent systematic review of improved biomass stoves (without chimneys) (Pope et al. 2021).

Several considerations are important in weighing the potentials of improved ventilation against those of ICS as a policy instrument to reduce HAP. First, only ICS may provide highly relevant co-benefits for forests, climate, women's time use, and household budgets if they reduce fuel consumption. Second, only *clean* stoves abolish HAP, whereas ventilation channels the aerosols outdoors, away from people. Third, improved ventilation in form of windows and doors can plausibly be a longer-term investment whereas use of ICS is limited to their lifespans and conditioned on their correct use.

There are several limitations to the findings of this chapter. First and foremost, given my non-experimental identification strategy, there remains a risk that my results are not causal. Despite the high robustness and conceptual foundation of my findings, this questions their internal validity. Second, while my sample is plausibly representative for rural and poor households in arid and dusty regions of West Africa, my findings may not be externally valid beyond similar contexts. Most importantly, effectiveness of ventilation is conditioned on the quality of ambient air (Zhou et al., 2011, Patel et al. 2017, Mönkkönen et al. 2005, Shibata et al. 2014, Saksena et al. 2003), i.e., ventilation can worsen indoor air in highly polluted (urban) settings. Moreover, security and privacy concerns can impede effective use of existent ventilation infrastructure (Muindi et al. 2016, Lueker et al. 2020). Season and weather, including ventilation-enhancing winds but also pollution-enhancing dust storms, can alter use and effectiveness of ventilation (Kulshreshtha and Khare 2011, Nayek and Padhy 2017). Details in kitchen structure, such as kitchen volume, beveled roofs, or natural ventilation paths inside and outside of housing will theoretically impact the pollution reduction potentials of ventilation. Additionally, location of the kitchen relative to other living spaces and behavioral responses to interventions will be decisive for people's pollution exposures.

My findings, in line with Smith et al. (1983), suggest that cooking fuels, stoves, and housing ventilation need to be considered holistically. This would allow for refined targeting of *improved* stoves to households with good housing ventilation, and of *clean* stoves to those with *poor* ventilation. In doing so, it is important to consider potential distributional effects of such targeted policies, as income and ventilation conditions are likely systematically and non-linearly related to each other. A more holistic view on cooking environments could also induce policies to directly improve housing ventilation or to raise awareness about its benefits. Lastly, my findings call upon research and policy debates to consider housing systematically to improve our understanding, and our means of overcoming, the myriad of burdens of traditional cooking.

References Chapter 3

- Albalak, Rachel, A. Roberto Frisancho, and Gerald J. Keeler.** 1999. Domestic biomass fuel combustion and chronic bronchitis in two rural Bolivian villages. *Thorax* 54(11): 1004-1008.
- Amegah, Adeladza K., Reginald Quansah, and Jouni J. K. Jaakkola.** 2014. Household air pollution from solid fuel use and risk of adverse pregnancy outcomes: a systematic review and meta-analysis of the empirical evidence. *PloS One* 9(12): e113920.
- Barnes, Brendon R.** 2014. Behavioural Change, Indoor Air Pollution and Child Respiratory Health in Developing Countries: A Review. *International Journal of Environmental Research and Public Health* 11(5): 4607-4618.
- Bensch, Gunther, and Jörg Peters.** 2015. The intensive margin of technology adoption—Experimental evidence on improved cooking stoves in rural Senegal. *Journal of health economics*, 42, 44-63.
- Bensch, Gunther, and Jörg Peters.** 2020. One-off grants and long-run adoption – Experimental evidence on improved cooking stoves in Senegal. *American Journal of Agricultural Economics* 102(1): 72-90.
- Bensch, Gunther, Michael Grimm, and Jörg Peters.** 2015. Why do households forego high returns from technology adoption? Evidence from improved cooking stoves in Burkina Faso. *Journal of Economic Behavior & Organization* 116: 187-205.
- Boadi, Kwasi Owusu, and Markku Kuitunen.** 2006. Factors affecting the choice of cooking fuel, cooking place and respiratory health in the Accra metropolitan area, Ghana. *Journal of Biosocial Science* 38(3): 403.
- Bradley, Robert H., and Diane L. Putnick.** 2012. Housing quality and access to material and learning resources within the home environment in developing countries. *Child Development* 83(1): 76-91.
- Buchner, Hannes, and Eva A. Rehfuess.** 2015. Cooking and season as risk factors for acute lower respiratory infections in African children: a cross-sectional multi-country analysis. *PLoS One*, 10(6): e0128933.
- Burnett, Richard T., C. Arden Pope III, Majid Ezzati, Casey Olives, Stephen S. Lim, Sumi Mehta, ..., and Aaron Cohen.** 2014. An integrated risk function for estimating the global burden of disease attributable to ambient fine particulate matter exposure. *Environmental Health Perspectives* 122(4): 397-403.
- Cattaneo, Matias D., Sebastian Galiani, Paul J. Gertler, Sebastian Martinez, and Rocio Titiunik.** 2009. Housing, health, and happiness. *American Economic Journal: Economic Policy* 1(1): 75-105.
- Chafe, Zoë A., Michael Brauer, Zbigniew Klimont, Rita Van Dingenen, Sumi Mehta, Shilpa Rao, ..., and Kirk R. Smith.** 2014. Household cooking with solid fuels contributes to ambient PM_{2.5} air pollution and the burden of disease. *Environmental Health Perspectives* 122(12): 1314-1320.
- Dedman, Daniel J., David Gunnell, George D. Smith, and Stephen Frankel.** 2001. Childhood housing conditions and later mortality in the Boyd Orr cohort. *Journal of Epidemiology & Community Health* 55(1): 10-15.
- Dherani, Mukesh, Daniel Pope, Maya Mascarenhas, Kirk R Smith, Martin Weber, and Nigel Bruce.** 2008. Indoor air pollution from unprocessed solid fuel use and pneumonia risk in children aged under five years: a systematic review and meta-analysis. *Bulletin of the World Health Organization*, 86: 390-398C.

Ezzati, Majid, and Daniel M. Kammen. 2002. The health impacts of exposure to indoor air pollution from solid fuels in developing countries: knowledge, gaps, and data needs. *Environmental health perspectives* 110(11): 1057-1068.

Filmer, Deon, and Lant H. Pritchett. 2001. Estimating wealth effects without expenditure data – or tears: an application to educational enrollments in states of India. *Demography* 38(1): 115-132.

Galiani, Sebastián, Paul Gertler, Ryan Cooper, Sebastian Martinez, Adam Ross, and Raimundo Undurraga. 2017. Shelter from the storm: Upgrading housing infrastructure in Latin American slums. *Journal of Urban Economics* 98: 187-213.

Grieshop, Andrew P., Julian D. Marshall, and Milind Kandlikar. 2011. Health and climate benefits of cookstove replacement options. *Energy Policy* 39(12): 7530-7542.

Hanna, Rema, Esther Duflo, and Michael Greenstone. 2016. Up in smoke: the influence of household behavior on the long-run impact of improved cooking stoves. *American Economic Journal: Economic Policy* 8(1): 80-114.

Harris, Richard, and Godwin Arku. 2006. Housing and economic development: The evolution of an idea since 1945. *Habitat International* 30(4): 1007-1017.

IEA, IRENA, UNSD, World Bank, and WHO. 2020. Tracking SDG 7: The Energy Progress Report. World Bank, Washington DC. https://trackingsdg7.esmap.org/data/files/download/documents/tracking_sdg_7_2020-full_report_-_web_0.pdf.

IEA. 2020. SDG7: Data and Projections. <https://www.iea.org/reports/sdg7-data-and-projections>.

Imbens, Guido. W. 2003. Sensitivity to exogeneity assumptions in program evaluation. *American Economic Review* 93(2): 126-132.

ISO (International Organization for Standardization). 2018. Clean Cookstoves and Clean Cooking Solutions: Harmonized Laboratory Test Protocols, Part 3: Voluntary Performance Targets for Cookstoves Based On Laboratory Testing. Technical Report ISO/TR 19867. ISO, Geneva.

Jagger, Pamela, and Carolina Perez-Heydrich. 2016. Land use and household energy dynamics in Malawi. *Environmental Research Letters* 11(12): 125004.

Jeuland, Marc A., and Subhrendu K. Pattanayak. 2012. Benefits and costs of improved cookstoves: assessing the implications of variability in health, forest and climate impacts. *PLoS One* 7(2): e30338.

Jeuland, Marc, Subhrendu K. Pattanayak, and Jie Sheng Tan Soo. 2014. Preference Heterogeneity and Adoption of Environmental Health Improvements: Evidence from a Cookstove Promotion Experiment. Available at SSRN: <https://ssrn.com/abstract=2490530>.

Jeuland, Marc, Subhrendu K. Pattanayak, and Randall Bluffstone. 2015. The economics of household air pollution. *Annual Review of Resource Economics* 7(1): 81-108.

Jeuland, Marc A., T Robert Fetter, Yating Li, and Subhrendu K. Pattanayak. 2021. Is energy the golden thread? A systematic review of the impacts of modern and traditional energy use in low-and middle-income countries. *Renewable and Sustainable Energy Reviews* 135:110406.

Krzyzanowski, Michal, Joshua S. Apte, Sophie P. Bonjour, Michael Brauer, Aaron J. Cohen, and Annette M. Prüss-Ustun. 2014. Air pollution in the mega-cities. *Current Environmental Health Reports* 1(3): 185-191.

Kulshreshtha, Priyanka, and Mukesh Khare. 2011. Indoor exploratory analysis of gaseous pollutants and respirable particulate matter at residential homes of Delhi, India. *Atmospheric Pollution Research* 2(3): 337-350.

Langbein, Jörg, Jörg Peters, and Colin Vance. 2017. Outdoor cooking prevalence in developing countries and its implication for clean cooking policies. *Environmental Research Letters* 12(11): 115008.

Langbein, Jörg. 2017. Firewood, smoke and respiratory diseases in developing countries – the neglected role of outdoor cooking. *PLoS One* 12(6): e0178631.

Levine, David I., Theresa Beltramo, Garrick Blalock, Carolyn Cotterman, and Andrew M Simons. 2018. What impedes efficient adoption of products? Evidence from randomized sales offers for fuel-efficient cookstoves in Uganda. *Journal of the European Economic Association* 16(6): 1850-1880.

Lewis, Jessica J., and Subhrendu K. Pattanayak. 2012 Who adopts improved fuels and cookstoves? A systematic review. *Environmental Health Perspectives* 120: 637–45.

Lewis, Jessica J., Vasundhara Bhojvaid, Nina Brooks, Ipsita Das, Marc A. Jeuland, Omkar Patange, and Subhrendu K. Pattanayak. 2015. Piloting Improved Cookstoves in India, *Journal of Health Communication* 20(sup1): 28-42.

Lueker, Justin, Ronita Bardhan, Ahana Sarkar, and Leslie Norford. 2020. Indoor air quality among Mumbai's resettled populations: Comparing Dharavi slum to nearby rehabilitation sites. *Building and Environment* 167, 106419.

MEDER (Ministère de l'Energie et du Développement des Energies Renouvelables). 2015. *Plan d'actions National des Energies Renouvelables (PANER) Senegal – Période [2015-2010/2030]*. https://www.se4all-africa.org/fileadmin/uploads/se4all/Documents/Country_PANER/Senegal_Plan_d_Actions_National_des_Energies_Renouvelables_.pdf.

Mobarak, Ahmed Mushfiq, Puneet Dwivedi, Robert Bailis, Lynn Hildemann, and Grant Miller. 2012. Low demand for nontraditional cookstove technologies. *Proceedings of the National Academy of Sciences of the United States of America* 109(27): 10815-10820.

Mönkkönen, P., P. Pai, A. Maynard, K.E.J. Lehtinen, K. Hämeri, P. Rechkemmer, ..., and M. Kulmala. 2005. Fine particle number and mass concentration measurements in urban Indian households. *Science of the Total Environment*, 347(1-3), 131-147.

Mortimer, Kevin, Chifundo B. Ndamala, Andrew W. Naunje, Jullita Malava, Cynthia Katundu, William Weston, ..., and Stephen B. Gordon. 2017. A cleaner burning biomass-fuelled cookstove intervention to prevent pneumonia in children under 5 years old in rural Malawi (the Cooking and Pneumonia Study): a cluster randomised controlled trial. *The Lancet* 389(10065): 167-175.

Muindi, Kanyiva, Elizabeth Kimani-Murage, Thaddaeus Egondi, Joacim Rocklov, and Nawi Ng. 2016. Household air pollution: sources and exposure levels to fine particulate matter in Nairobi slums. *Toxics* 4(3): 12.

Nayek, Sukanta, and Pratap Kumar Padhy. 2017. Daily personal exposure of women cooks to respirable particulate matters during cooking with solid bio-fuels in a rural community of West Bengal, India. *Aerosol and Air Quality Research* 17(1): 245-252.

Oster, Emily. 2019. Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business and Economic Statistics* 37(2): 187-204.

Patel, Sameer, Jiayu Li, Apoorva Pandey, Shamsh Pervez, Rajan K. Chakrabarty, and Pratim Biswas. 2017. Spatio-temporal measurement of indoor particulate matter concentrations using a wireless network of low-cost sensors in households using solid fuels. *Environmental research* 152: 59-65.

Pattanayak, Subhrendu K., Marc A. Jeuland, Jessica J. Lewis, Vasundhara Bhojvaid, Nina Brooks, Abhishek Kar, ..., and Veerabhadran Ramanathan. 2016. Cooking up change in the Himalayas: experimental evidence on cookstove promotion. Duke Environmental and Energy Economics Working Paper Series, Working Paper EE 16-03.

Po, June Y., J. Mark FitzGerald, and Chis Carlsten. 2011. Respiratory disease associated with solid biomass fuel exposure in rural women and children: systematic review and meta-analysis. *Thorax* 66(3): 232-239.

Pope, Daniel, Nigel Bruce, Mukesh Dherani, Kirstie Jagoe, and Eva Rehfuess. 2017. Real-life effectiveness of 'improved' stoves and clean fuels in reducing PM2.5 and CO: systematic review and meta-analysis. *Environment International* 101: 7-18.

Pope, Daniel, Michael Johnson, Nigel Fleeman, Kirstie Jagoe, Rui Duarte, Michelle Maden, Ramona Ludolph, ... and Jessica J. Lewis. 2020. Are cleaner cooking solutions clean enough? A systematic review and meta-analysis of particulate and carbon monoxide concentrations and exposures. Unpublished manuscript.

Rehfuess, Eva A., Lia Tzala, Nicky Best, David J. Briggs, and Mike Joffe. 2009. Solid fuel use and cooking practices as a major risk factor for ALRI mortality among African children. *Journal of Epidemiology and Community Health* 63(11): 887-892.

Romieu, Isabelle, Horacio Riojas-Rodríguez, Adriana Teresa Marrón-Mares, Astrid Schilman, Rogelio Perez-Padilla, Omar Masera. 2009. Improved biomass stove intervention in rural Mexico: impact on the respiratory health of women. *American Journal of Respiratory and Critical Care Medicine* 180(7): 649-656.

Rosenbaum, Paul R., and Rubin, Donald B. 1983. Assessing sensitivity to an unobserved binary covariate in an observational study with binary outcome. *Journal of the Royal Statistical Society: Series B (Methodological)* 45(2): 212-218.

Saksena, Sumeet, PB Singh, Raj Kumar Prasad, Rakesh Prasad, Preeti Malhotra, Veena Joshi, and R.S. Patil. 2003. Exposure of infants to outdoor and indoor air pollution in low-income urban areas – a case study of Delhi. *Journal of Exposure Science & Environmental Epidemiology* 13(3): 219-230.

Sambandam, Sankar, Kalpana Balakrishnan, Santu Ghosh, Arulselvan Sadasivam, Satish Madhav, Rengaraj Ramasamy, ..., and Veerabhadran Ramanathan. 2015. Can currently available advanced combustion biomass cook-stoves provide health relevant exposure reductions? Results from initial assessment of select commercial models in India. *EcoHealth* 12(1): 25-41.

Shibata, Tomoyuki, James L. Wilson, Lindsey M. Watson, Alyse LeDuc, Can Meng, Ansariadi, ..., and Alimin Maidin. 2014. Childhood acute respiratory infections and household environment in an eastern Indonesian urban setting. *International Journal of Environmental Research and Public Health* 11(12): 12190-12203.

Shupler, Matthew, Perry Hystad, Aaron Birch, Daniel Miller-Lionberg, Matthew Jeronimo, Raphael E Arku,..., and Michael Brauer. 2020. Household and personal air pollution exposure measurements from 120 communities in eight countries: results from the PURE-AIR study. *The Lancet Planetary Health*, 4(10): e451-e462.

Simon, Gregory L., Rob Bailis, Jill Baumgartner, Jasmine Hyman, and Arthur Laurent. 2014. Current debates and future research needs in the clean cookstove sector. *Energy for Sustainable Development* 20: 49-57.

Singh, Ashish, Bhushan Tuladhar, Karuna Bajracharya, Ajay Pillarisetti. 2012. Assessment of effectiveness of improved cook stoves in reducing indoor air pollution and improving health in Nepal. *Energy for Sustainable Development* 16(4): 406-414.

Smith, Kirk R., A. L. Aggarwal, and R. M. Dave. 1983. Air pollution and rural biomass fuels in developing countries: a pilot village study in India and implications for research and policy. *Atmospheric Environment* (1967) 17(11): 2343-2362.

Smith, Kirk R., John P. McCracken, Martin W. Weber, Alan Hubbard, Alisa Jenny, Lisa M. Thompson, ..., and Nigel Bruce. 2011. Effect of reduction in household air pollution on childhood pneumonia in Guatemala (RESPIRE): a randomised controlled trial. *The Lancet* 378(9804): 1717-1726.

Smith, Kirk R., Nigel Bruce, Kalpana Balakrishnan, Heather Adair-Rohani, John Balmes, Zoë Chafe, ..., and HAP CRA Risk Expert Group. 2014. Millions dead: how do we know and what does it mean? Methods used in the Comparative Risk Assessment of Household Air Pollution. *Annual Review of Public Health* 35: 185-206.

Teune, Bastiaan, Hoang Thanh Ha, Daniel Salinas, Kevin McLean, and Rob Bailis. 2020. Low-cost interventions to reduce emissions and fuel consumption in open wood fires in rural communities. *Energy for Sustainable Development*, 58: 119-128.

WHO (World Health Organization). 2006. WHO Air quality guidelines for particulate matter, ozone, nitrogen dioxide and sulfur dioxide: global update 2005: summary of risk assessment. World Health Organization, Geneva. <https://apps.who.int/iris/handle/10665/69477>

WHO (World Health Organization). 2008. Evaluating household energy and health interventions: A catalogue of methods. World Health Organization, Geneva. https://www.who.int/indoorair/publications/methods/full_catalogue_method.pdf.

WHO (World Health Organization). 2016. Burning opportunity: clean household energy for health, sustainable development and wellbeing of women and children. World Health Organization, Geneva. <https://apps.who.int/iris/handle/10665/204717>.

Zaman, Sojib Bin, Naznin Hossain, Salamat Khandker. 2017. Impact of improved cooking stove on maternal health in rural Bangladesh: A quasi-experimental study. *Journal of Medical Research and Innovation* 1(3): 1-9.

Zhou, Zheng, Kathie L. Dionisio, Raphael E. Arku, Audrey Quaye, Allison F. Hughes, Jose Vallarino, ..., Majid Ezzati. 2011. Household and community poverty, biomass use, and air pollution in Accra, Ghana. *Proceedings of the National Academy of Sciences* 108(27): 11028-11033.

Appendix Chapter 3

Appendix 3A: Systematic Review

Table 3A.1: Search string

Ventilation ¹¹¹
ventilat*, airing, aeration, “air circulation”, chimney*, fan, hood*, vent*, outdoor, outside, *closed, open*, window*, door*, flue*, wall*, “kitchen characteristic*”, “kitchen type*”, “kitchen structure*”, roof*, ARTI, Parvati, Laxmi, BCSIR, Casamiga, Chispa, Tortillera, Plancha, Co2balance, DA, Anandi, DC-I, DC-II, SARAL, Sukhad, “Dos por Tres”, “Eco Efficient*”, “Estufa”, EcoStove, “San Juan del Sur”, Ecostufa, Repisa, EfCoiTa, “Doña Dora”, Hiteca, Palermo, FN, “Foladi Duo”, GAMA1411, “Gari Elephant”, GNG, HEERS, Hoodstove, Himalayan, Inkafogao, Inkawasi, Suita, TAWA, “Iron Man”, Jiangsu, “Jiko Safi”, Jinqilin, “JUMBO ZAMA”, Kang, “Kuna Yala”, KuniTatu, Malena, “MBS 9”, “Mera-Mera”, Onil, Openut, Patsari, Chefina, Prakti, Lorena, SaverPro, Envirofit, Griddle, Hunter, “Super Saver”, Supreme, Tsinghua, Wonder, Zhiqi, Zoom
Air pollution
Emission*, concentration*, exposure*, air pollut*, “air quality”, smoke, particle*, “particulate matter”, carbon, CO, PM, NOx, SO2, “carbon monoxide*”, oxide*, “volatile organic*”, dioxin
Pollution source and fuel
Fire, firewood, charcoal, coal, wood, biofuel*, woodfuel*, biomass, “solid fuel*”, LPG, “liquified petroleum gas”, gas, kerosene, fuelwood, fuel*, cookstove*, “cooking stove*”, stove*, combustion
Activity
Cook*, kitchen*, stove*
Cooking location
Kitchen, indoor, home, household, inside
Countries
Africa*, “Latin America*”, “Central America*”, “South America*”, Asia*, “South Asia*”, “low income”, “less developed countr*”, “developing countr*”, “emerging market*”, “emerging econom*”, “least developed countr*”, LIC*, LDC*, “third world”, “global south”, “middle income”, LMIC, Afghanistan, Albania, Algeria, Angola, Argentina, Armenia, Azerbaijan, Bangladesh, Belarus, Belize, Benin, Bhutan, Bolivia, Bosnia, Botswana, Brazil, Bulgaria, “Burkina Faso”, Burundi, “Cabo Verde”, “Cape Verde”, Cambodia, Cameroon, “Central African Republic”, Chad, China, Colombia, Comoros, Congo, “Costa Rica”, “Côte d'Ivoire”, “Cote d'Ivoire”, “Ivory Coast”, Cuba, Djibouti, Dominica, “Dominican Republic”, Ecuador, Egypt, “El Salvador”, “Equatorial Guinea”, Eritrea, Ethiopia, Fiji, Gabon, Gambia, Georgia, Ghana, Grenada, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, India, Indonesia, Iran, Iraq, Jamaica, Jordan, Kazakhstan, Kenya, Kiribati, “North Korea”, DPRK, Kosovo, Kyrgyz*, Lao*, Lebanon, Lesotho, Liberia, Libya, Macedonia, Madagascar, Malawi, Malaysia, Maldives, Mali, “Marshall Islands”, Mauritania, Mauritius, Mexico, Micronesia, Moldova, Mongolia, Montenegro, Morocco, Mozambique, Myanmar, Namibia, Nepal, Nicaragua, Niger, Nigeria, Pakistan, Palau, Panama, “Papua New Guinea”, Paraguay, Peru, Philippines, Romania, Russia*, Rwanda, Samoa, “São Tomé and Príncipe”, “São Tomé and Principe”, “Sao Tome and Principe”, Senegal, Serbia, “Sierra Leone”, “Solomon Islands”, Somalia, “South Africa”, “South Sudan”, “Sri Lanka”, “St* Lucia”, “Saint Lucia”, “St* Vincent”, “Saint Vincent”, “Saint Vincent and the Grenadines”, “St* Vincent and the Grenadines”, Sudan, Suriname, Swaziland, Syria, Tajikistan, Tanzania, Thailand, Tibet*, Timor-Leste, “East Timor”, Togo, Tonga, Tunisia, Turkey, Turkmenistan, Tuvalu, Uganda, Ukraine, Uzbekistan, Vanuatu, Venezuela, Vietnam, “West Bank”, Gaza*, Yemen, Zambia, Zimbabwe”

Note: The search string identified studies that include any of the listed terms in each of the categories in their title, abstract or keywords. The criteria were the same across databases, but slightly adapted to the database’s search functions.

¹¹¹ I included stove names of all chimney stoves listed in the Clean Cooking Alliance’s Clean Cooking Catalog.

Table 3A.2: Records in Systematic Review

Study	Title	Authors	Year	Journal
1	Assessment of PM10 concentrations from domestic biomass fuel combustion in two rural Bolivian highland villages	Albalak, R.; Keeler, G.J.; Frisancho, A.R.	1999	Environmental Science And Technology
2	Indoor PM and CO concentrations in rural Guizhou, China	Alnes, L.W.H.; Mestl, H.E.S.; Berger, J.	2014	Energy For Sustainable Development
3	State and national household concentrations of PM2.5 from solid cookfuel use: Results from measurements and modeling in India for estimation of the global burden of disease	Balakrishnan, K.; Ghosh, S.; Ganguli, B.	2013	Environmental Health
4	Exposure assessment for respirable particulates associated with household fuel use in rural districts of Andhra Pradesh, India	Balakrishnan, K.; Sambandam, S.; Ramaswamy, P.	2004	Journal Of Exposure Analysis And Environmental Epidemiology
5	Daily average exposures to respirable particulate matter from combustion of biomass fuels in rural households of Southern India	Balakrishnan, K.; Sankar, S.; Parikh, J.	2002	
6	Patterns of domestic exposure to carbon monoxide and particulate matter in households using biomass fuel in Janakpur, Nepal	Bartington, S.E.; Bakolis, I.; Devakumar, D.	2017	Environmental Pollution
7	Patterns and predictors of personal exposure to indoor air pollution from biomass combustion among women and children in rural China	Baumgartner, J.; Schauer, J.J.; Ezzati, M.	2011	Indoor Air
8	Indoor air pollution from particulate matter emissions in different households in rural areas of Bangladesh	Begum, B.A.; Paul, S.K.; Dildar H.M.	2009	Building And Environment
9	Impact of improved stoves, house construction and child location on levels of indoor air pollution exposure in young Guatemalan children	Bruce, N.; Mccracken, J.; Albalak, R.	2004	Journal Of Exposure Analysis And Environmental Epidemiology
10	Indoor air pollution, cookstove quality, and housing characteristics in two Honduran communities	Clark, M.L.; Reynolds, S.J.; Burch, J.B.	2010	Environmental Research
11	Impaired lung function in individuals chronically exposed to biomass combustion	Da Silva, L.F.F.; Saldiva, S.R.D.M.; Saldiva, P.H.N.	2012	Environmental Research
12	Indoor air quality for poor families: New evidence from Bangladesh	Dasgupta, S.; Huq, M.; Khaliquzzaman, M.	2004	The World Bank
13	Lessons from rural madagascar on improving air quality in the kitchen	Dasgupta, S.; Martin, P.; Samad, H.A.	2015	Journal Of Environment And Development
14	Characteristics of indoor air pollution and estimation of respiratory dosage under varied fuel-type and kitchen-type in the rural areas of Telangana state in India	Deepthi, Y.; Shiva Nagendra, S.M.; Gummadi, S.N.	2019	Science Of The Total Environment
15	Reducing indoor air pollution in rural households in Kenya: Working with communities to find solutions	Doig, A.; Bates, L.; Bruce, N.	2001	
16	Outdoor, indoor, and personal black carbon exposure from cookstoves burning solid fuels	Downward, G.S.; Hu, W.; Rothman, N.	2016	Indoor Air
17	Indoor pollution in high-altitude dwellings: An assessment of affecting factors across four Sherpa villages in the Khumbu region, Nepal	Duo, E.; Bruno, R.M.; Basnyat, B.	2018	Indoor And Built Environment
18	Women exposure to household air pollution after an improved cookstove program in rural San Luis Potosi, Mexico	EstéVez-García, J.A.; Schilman, A.; Riojas-Rodríguez, H.	2020	Science Of The Total Environment
19	Household air pollution exposure and associations with household characteristics among biomass cookstove users in Puno, Peru	Fandiño-Del-Rio, M.; Kephart, J.L.; Williams, K.N.	2020	Environmental Research

Study	Title	Authors	Year	Journal
20	Levels and determinants of fine particulate matter and carbon monoxide in kitchens using biomass and non-biomass fuel for cooking	Fatmi, Z.; Ntani, G.; Coggon, D.	2020	International Journal Of Environmental Research And Public Health
21	Daily average exposures to carbon monoxide from combustion of biomass fuels in rural households of Haryana, India	Gautam, S.; Pillarisetti, A.; Yadav, A.	2019	Environment Development And Sustainability
22	Seasonal concentrations and determinants of indoor particulate matter in a low-income community in Dhaka, Bangladesh	Gurley, E.S.; Salje, H.; Homaira, N.	2013	Environmental Research
23	Chimney stoves modestly improved indoor air quality measurements compared with traditional open fire stoves: Results from a small-scale intervention study in rural Peru	Hartinger, S.M.; Commodore, A.A.; Hattendorf, J.	2013	Indoor Air
24	Characteristics of indoor air pollution in rural mountainous and rural coastal communities in Indonesia	Huboyo, H.S.; Tohno, S.; Lestari, P.	2014	Atmospheric Environment
25	Non-invasive measurement of carbon monoxide in rural Indian woman exposed to different cooking fuel smoke	Joon, V.; Kumar, K.; Bhattacharya, M.	2014	Aerosol And Air Quality Research
26	Indoor air pollution and health of children in biomass fuel-using households of Bangladesh: comparison between urban and rural areas	Khalequzzaman, M.; Kamijima, M.; Sakai, K.	2011	Environmental Health And Preventive Medicine
27	Low correlation between household carbon monoxide and particulate matter concentrations from biomass-related pollution in three resource-poor settings	Klasen, E.M.; Wills, B.; Naithani, N.	2015	Environmental Research
28	Exposure to indoor and outdoor air pollution among children under five years old in urban area	Kouao, A.K.R.; N'Datchoh, E.T.; Yoboue, V	2019	Global Journal Of Environmental Science And Management-Gjesm
29	Indoor exploratory analysis of gaseous pollutants and respirable particulate matter at residential homes of Delhi, India	Kulshreshtha, P.; Khare, M.;	2011	Atmospheric Pollution Research
30	Pollutant levels at cooking place and their association with respiratory symptoms in women in a rural area of Delhi-NCR	Kumar, R.; Singh, K.; Nagar, S.	2015	The Indian Journal Of Chest Diseases And Allied Sciences
31	Real-time particulate and CO concentrations from cookstoves in rural households in Udaipur, India	Leavey, A.; Londeree, J.; Priyadarshini, P.	2015	Environmental Science And Technology
32	Pollutant concentrations within households in Lao PDR and association with housing characteristics and occupants' activities	Morawska, L.; Mengersen, K.; Wang, H.	2011	Environmental Science And Technology
33	Indoor air pollution and risk of lung cancer among Chinese female non-smokers	Mu, L.; Liu, L.; Niu, R.	2013	Cancer Causes And Control
34	Indoor particulate matter in developing countries: A case study in Pakistan and potential intervention strategies	Nasir, Z.A.; Colbeck, I.; Ali, Z.	2013	Environmental Research Letters
35	Daily personal exposure of women cooks to respirable particulate matters during cooking with solid bio-fuels in a rural community of west Bengal, India	Nayek, S.; Padhy, P. K.;	2017	Aerosol And Air Quality Research
36	Approximation of personal exposure to fine particulate matters (PM 2.5) during cooking using solid biomass fuels in the kitchens of rural West Bengal, India	Nayek, S.; Padhy, P.K.;	2018	Environmental Science And Pollution Research International
37	Seasonal variation in outdoor, indoor, and personal air pollution exposures of women using wood stoves in the Tibetan Plateau: Baseline assessment for an energy intervention study	Ni, K.; Carter, E.; Schauer, J.J.	2016	Environment International
38	Exposures from cooking with biofuels: Pollution monitoring and analysis for rural Tamil Nadu, India	Parikh, J.;Balakrishnan, K.;Laxmi, V.	2001	
39	Associations between household air pollution and reduced lung function in women and children in rural southern India	Patel, S.; Leavey, A.; Sheshadri, A.	2018	Journal Of Applied Toxicology: Jat

Study	Title	Authors	Year	Journal
40	Sri Lanka pilot study to examine respiratory health effects and personal PM2.5 exposures from cooking indoors	Phillips, M.J.; Smith, E.A.; Mosquin, P.L.	2016	International Journal Of Environmental Research And Public Health
41	PM2.5 in household kitchens of Bhaktapur, Nepal, using four different cooking fuels	Pokhrel, A.K.; Bates, M.N.; Acharya, J.	2015	Atmospheric Environment
42	Household firewood use and the health of children and women of Indian communities in Chiapas, Mexico	Riojas-Rodríguez, H.; Romano-Riquer, P.; Santos-Burgoa, C.	2001	International Journal Of Occupational And Environmental Health
43	Indoor air pollution from biomass combustion and respiratory symptoms of women and children in a Zimbabwean village	Rumchev, K.; Spickett, J.T.; Brown, H.L.	2007	Indoor Air
44	Exposure of infants to outdoor and indoor air pollution in low-income urban areas - a case study of Delhi	Saksena, S.; Singh, P.B.; Prasad, R.K.	2003	Journal Of Exposure Analysis And Environmental Epidemiology
45	Indoor air pollution in coastal houses of southern Philippines	Saksena, S.; Subida, R.; Buttner, L.	2007	Indoor And Built Environment
46	Impact of intervention of biomass cookstove technologies and kitchen characteristics on indoor air quality and human exposure in rural settings of India	Sharma, D.; Jain, S.;	2019	Environment International
47	Household air pollution from various types of rural kitchens and its exposure assessment	Sidhu, M.K.; Ravindra, K.; Mor, S.	2017	Science Of The Total Environment
48	Determining particulate matter and black carbon exfiltration estimates for traditional cookstove use in rural Nepalese village households	Soneja, S.I.; Tielsch, J.M.; Curriero, F.C.	2015	Environmental Science And Technology
49	Open fire ovens and effects of in-home lavash bread baking on carbon monoxide exposure and carboxyhemoglobin levels among women in rural Armenia	Tadevosyan, A.; Mikulski, M.A.; Wallis, A.B.	2020	Indoor Air
50	Monitoring and modeling of household air quality related to use of different Cookfuels in Paraguay	Tagle, M.; Pillarisetti, A.; Hernandez, M.T.	2019	Indoor Air
51	Carbon monoxide concentrations in outdoor wood-fired kitchens in Ouagadougou, Burkina Faso-implications for women's and children's health	Thorsson, S.; Holmer, B.; Andjelic, A.	2014	Environmental Monitoring And Assessment
52	Personal and indoor exposure to PM and polycyclic aromatic hydrocarbons in the southern highlands of Tanzania: A pilot-scale study	Titcombe, M.E.; Simcik, M.;	2011	Environmental Monitoring And Assessment
53	Personal exposures to fine particulate matter and black carbon in households cooking with biomass fuels in rural Ghana	Van Vliet, E.D.S.; Asante, K.; Jack, D.W.	2013	Environmental Research
54	Improving indoor air quality for poor families: A controlled experiment in Bangladesh	Wheeler, D.; Khaliquzzaman, M.; Huq, M.	2007	World Bank Policy Research Working Paper Series
55	Maternal exposure to carbon monoxide and fine particulate matter during pregnancy in an urban Tanzanian cohort	Wylie, B.J.; Kishashu, Y.; Matechi, E.	2017	Indoor Air
56	Biomass smoke in Burkina Faso: What is the relationship between particulate matter, carbon monoxide, and kitchen characteristics?	Yamamoto, S.S.; Louis, V.R.; Sie, A.	2013	Environmental Science And Pollution Research
57	Household air pollution and personal exposure from burning firewood and yak dung in summer in the eastern Tibetan Plateau	Ye, W.; Saikawa, E.; Avramov, A.	2020	Environmental Pollution
58	Carbonaceous particulate matter air pollution and human exposure from indoor biomass burning practices	Zhong, J.; Ding, J.; Su, Y.	2012	Environmental Engineering Science
59	Household and community poverty, biomass use, and air pollution in Accra, Ghana	Zhou, Z.; Dionisio, K.L.; Arku, R.E.	2011	Proceedings Of The National Academy Of Sciences Of The United States Of America

Text extension 3A.1: Studies in Systematic Review

Analysis of the 59 included papers yields several interesting lessons. First, the literature is spread across multiple scientific disciplines and geographies, starting in the early 2000's. The articles were published between 1999 and 2020, and roughly half of them after 2012. They were published in 30 distinct, mostly environmental and health field journals,¹¹² but the work is often multidisciplinary, and is addressed by epidemiological, public health and medical scientists, engineers, and environmental (health) scientists.

Figure 3A.1 illustrates that the evidence is geographically widespread but clustered in Eastern South Asia and China. In line with high prevalence of biomass cooking in rural areas, most studies (85 percent) study air pollution in peri-urban or rural households.

Figure 3A.1: Geographical coverage of studies



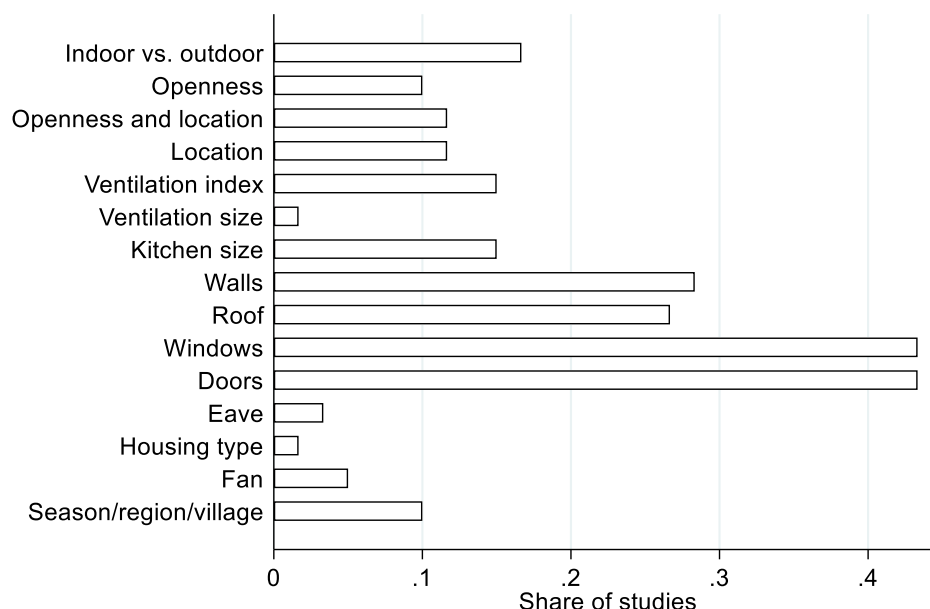
Note: n=58; one cross-country study (on Kenya, Nepal, Peru) is not displayed.

Second, my analysis shows that we lack consensus on how to approximate housing ventilation. Figure 3A.2 shows, for example, that roughly 40 percent of included papers look at each of window and door characteristics. However, these ventilation proxies are defined in myriad ways. For example, windows and doors may include their number, their size, a categorization of them, or an indicator variable for whether they were observed to be left open. Roof and wall indicators among others include the number of roofs/walls, a wide range of materials, or a combination of the two. Housing ventilation indices combine wall and roof materials, windows and doors, or other characteristics of the housing structure. Several further proxies are used in addition, including very rough indicators which according to the authors proxy for better or worse housing ventilation, such as indicators for season, region, or village. According to the

¹¹² The most frequent journals are: Indoor Air (7), Environmental Research (6), and Environmental Science and Technology (4).

authors, season can be used as a proxy for ventilation as it determines, for example whether a household cooks outdoors (in the dry season) or indoors (in the rainy season). Similarly, there are regions or villages in which households cook exclusively indoors or where kitchens are poorly ventilated, while in other regions or villages cooking is done exclusively outdoors or in semi-opened kitchens.

Figure 3A.2: Ventilation indicators applied in studies



Note: Within each sub-category shown above, there is considerable heterogeneity in the specific measures used to characterize the feature.

Third, the focus of much of the literature is on measuring the relationship between ventilation and kitchen pollution (78 percent of estimates), as opposed to exposure of a specific household member (31 percent), pollution in the living space (27 percent), outdoor pollution (15 percent), and pollution in a child's room (seven percent) or the main bedroom (five percent).

Fourth, the 59 studies examine distinct combinations of pollutant, measurement area, and housing ventilation proxy, resulting in a total of 236 distinct estimates. Specifically, one study may look at CO pollution in a living room and proxy ventilation by existence of a fan, whereas another study may observe women's personal exposure to PM and proxy ventilation by the size of windows. Given the substantial heterogeneity in the combination of these three variables, the evidence for consistent specifications is limited.

Fifth, research designs vary. For example, while 27 percent of studies provide a multivariate regression analysis (multi-factor ANOVA, multiple linear regression, quantile regression, fixed/random/mixed effects model, or similar), 30 percent conduct univariate statistical tests (one-way ANOVA, t-tests, Mann-Whitney-test, or similar), 43 percent compare means without statistical testing. Household sample sizes are often small. They vary between one and 824,

with a median sample size of 78. In some cases, results presentation is insufficient, where, for example, estimation methods are not outlined, ventilation proxies are theoretically unsound, comparison groups are systematically different from one another, or results are absent or unclear to the reader.

Table 3A.3: Higher ventilation and pollution in Systematic Review, share of studies

Panel A: Across pollutants (PM, CO) and monitored area (area, pollution exposure)

	Lower sig.	Lower insig.	Lower undef.	Higher sig.	Higher insig.	Higher undef.	N estimates	N studies
All studies	0.24	0.14	0.26	0.07	0.06	0.09	262.00	48.00
Sample size>100	0.39	0.26	0.00	0.11	0.12	0.00	98.00	20.00
Sample size>200	0.45	0.30	0.00	0.09	0.06	0.00	66.00	16.00
Sample size>300	0.40	0.40	0.00	0.05	0.07	0.00	40.00	8.00

Panel B: PM area pollution

	Lower sig.	Lower insig.	Lower undef.	Higher sig.	Higher insig.	Higher undef.	N estimates	N studies
All studies	0.27	0.13	0.31	0.06	0.05	0.10	145.00	34.00
Sample size>100	0.47	0.22	0.00	0.12	0.08	0.00	51.00	14.00
Sample size>200	0.49	0.24	0.00	0.12	0.02	0.00	41.00	11.00
Sample size>300	0.43	0.35	0.00	0.04	0.04	0.00	23.00	6.00

Panel C: CO area pollution

	Lower sig.	Lower insig.	Lower undef.	Higher sig.	Higher insig.	Higher undef.	N estimates	N studies
All studies	0.18	0.10	0.29	0.07	0.13	0.07	68.00	20.00
Sample size>100	0.27	0.23	0.00	0.05	0.32	0.00	22.00	6.00
Sample size>200	0.42	0.25	0.00	0.00	0.25	0.00	12.00	3.00
Sample size>300	0.17	0.50	0.00	0.00	0.33	0.00	6.00	1.00

Panel D: PM pollution exposure

	Lower sig.	Lower insig.	Lower undef.	Higher sig.	Higher insig.	Higher undef.	N estimates	N studies
All studies	0.30	0.21	0.09	0.09	0.03	0.15	33.00	13.00
Sample size>100	0.29	0.41	0.00	0.18	0.06	0.00	17.00	6.00
Sample size>200	0.33	0.56	0.00	0.11	0.00	0.00	9.00	3.00
Sample size>300	0.33	0.56	0.00	0.11	0.00	0.00	9.00	3.00

Panel E: CO pollution exposure

	Lower sig.	Lower insig.	Lower undef.	Higher sig.	Higher insig.	Higher undef.	N estimates	N studies
All studies	0.19	0.25	0.06	0.06	0.00	0.00	16.00	8.00
Sample size>100	0.38	0.25	0.00	0.13	0.00	0.00	8.00	4.00
Sample size>200	0.50	0.50	0.00	0.00	0.00	0.00	4.00	2.00
Sample size>300	1.00	0.00	0.00	0.00	0.00	0.00	2.00	1.00

Appendix 3B: Data and measurement

Table 3B.1: Sample sizes, by measurement and year

	Year 1	Year 2	Total
Pollution exposure	2	16	18
Kitchen pollution	114	102	216
Pollution exposure and kitchen pollution	125	77	202
Total	241	195	436

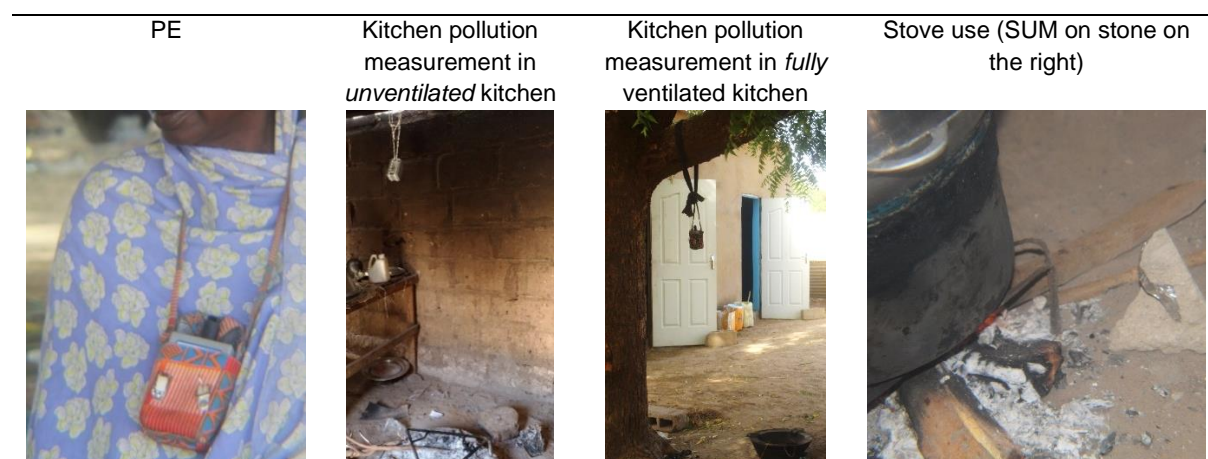
Note: The table shows that the samples of the two levels of particle measurements are different, albeit overlapping. I also have a slightly larger sample from year 1, due to malfunctioning meters in year 2.

Table 3B.2: Ventilation indicator, field categorization and aggregation

Indicator	(1) Categorization in the field	(2) Aggregation in analysis
Roof	- Solid roof, e.g., made of sheet metal, canvas, concrete	1 (no)
	- Solid roof with openings	
	- Permeable, e.g., made of bamboo or grass	2 (poor)
	- Permeable with openings	3 (substantial)
	- Open air	4 (full)
Wall	- Fully closed: Impermeable without openings	1 (no)
	- Fully closed: Impermeable with openings	
	- Fully closed: Permeable without openings	2 (poor)
	- Fully closed: Permeable with openings	
	- Semi-enclosed: 2 or 3 walls to the roof.	3 (substantial)
	- Semi-enclosed: 1 wall to the roof	
	- Open air	4 (full)
Openness	- No opening except for the door	1 (no)
	- Small openings	2 (poor)
	- Medium-sized openings	
	- Significant openings	3 (substantial)
	- Open air	4 (full)

Note: Permeable materials include, e.g., concrete, bricks, and mud; impermeable materials include, e.g., bamboo, grass, and boards. Our team classified kitchens in the field (1). I aggregate the categorizations further (2) to ensure sufficiently large groups, resulting in roof, walls, and openness indicators ranging from 1-4.

Figure 3B.1: Field photographs of MicroPEM and SUM measurements



Appendix 3C: Descriptive Statistics

Table 3C.1: Household, cooking, and measurement controls, by measurement sub-sample

	(1) Kitchen pollution	(2) Pollution exposure
(i) Study participant and household characteristics		
Age of Participant	32.43 (11.40)	32.62 (10.55)
Participant is homemaker	0.59	0.57
Participant is literate	0.16	0.18
HH is primarily Wolof	0.72	0.71
Participant has normal blood pressure	0.45	0.41
Participant has red eyes at least sometimes	0.19	0.18
HH size	11.87 (5.90)	12.10 (6.42)
HH has a private tap	0.68	0.66
HH has modern electricity	0.58	0.57
HH's normalized wealth index	0.04 (1.05)	0.02 (1.07)
(ii) Kitchen characteristics		
Kitchen volume=1	0.64	0.63
Kitchen volume=2	0.21	0.22
Kitchen volume=3	0.05	0.04
Kitchen volume=4	0.08	0.10
(iii) Cooking characteristics		
Dirtiest stove=traditional stove	0.75	0.64
Dirtiest stove=basic metal stove	0.09	0.09
Dirtiest stove=fuelwood ICS	0.14	0.17
Dirtiest stove=LPG stove	0.03	0.10
Share of cooking on OFS	0.67 (0.44)	0.67 (0.44)
Total cooking duration	332.60 (126.40)	337.55 (122.70)
Person-caterings per day	31.94 (20.16)	34.2 (24.16)
Treatment group: control	0.70	0.71
Treatment group: simple ICS	0.14	0.14
Treatment group: advanced ICS	0.16	0.16
(iv) Cooking behavior		
Burn agricultural waste at home	0.32	0.34
Participant avoids kitchen smoke	0.84 (0.36)	0.80 (0.39)
Smell neighbors' smoke weekly	0.35	0.30

...

Table 3C.1 continued

	(1) Kitchen pollution	(2) Pollution exposure
(v) Measurement controls		
Endline	0.42	0.42
Meter is MicroPEM	0.79	0.81
Share of cooking events with measurement	0.90 (0.23)	0.90 (0.32)
Number of main cooks	1.36 (0.69)	1.39 (0.71)
Participant was main cook	0.74	0.72
Participant was secondary cook	0.12	0.13
Meter daytime wearing (in %)	0.72 (0.19)	0.70 (0.19)
N	220	418

*Sd in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard deviations are in parentheses. The last block of variables (iv) shows measurement variables that will differ for the estimations on kitchen pollution and pollution exposure. Normal blood pressure is defined as (SYS<120 and DIA<80), as opposed to elevated pressure or hypertension stages, following the definition of the American Heart Association from 2017. The wealth index is generated via Principal Component Analysis (see, e.g., Filmer and Pritchett, 2001 and Kolenikov and Angeles 2004) using 19 variables, among others land holding, device ownership and livestock ownership. The index is normalized to a mean of zero and a standard deviation of 1. Meter daytime wearing is the share of daytime that participants effectively wore the MicroPEM as measured by the MicroPEMs internal accelerometer assuming 8h of sleep. As an indicator for secondary exposure to air pollution, I generate an indicator for whether participants report smelling neighbors' smoke at least weekly. The questions underlying the cooking behavior dummies are: "Do you regularly burn agricultural waste at home?" (Dummy for No), "What can you do to reduce burdens [of unclean cooking on your family's health, water sources and air quality]? Share of cooking events with measurement refers to the share of cooking events that were conducted in the kitchen with installed meter. The dirtiest stove is the dirtiest stove located close (<3m) to the meter for kitchen pollution measurement, and dirtiest stove used (self-reported) for personal exposure measurement. Volume category 1 is defined as smaller/equal 25m³, category 2 as between 25.1 and 50m³, category 3 as larger than 50m³, and category 4 as open air.*

Table 3C.2: Spearman monotone dependence between ventilation indicators

	Quartile ventilation	PC ventilation	Open air	Walls	Roof	Location
Quartile ventilation	1.00					
PC ventilation	0.82	1.00				
Open air	0.54	0.57	1.00			
Walls	0.82	0.80	0.58	1.00		
Roof	0.83	0.65	0.47	0.48	1.00	
Location	0.38	0.36	0.54	0.38	0.39	1.00

Appendix 3D: Kitchen pollution

Table 3D.1: Ventilation and kitchen pollution (PM_{2.5}): composite ventilation indicators

	(1) PM b/se	(2) PM b/se	(3) PM b/se	(4) PM b/se	(5) PM b/se	(6) PM b/se	(7) PM b/se	(8) PM b/se	(9) PM b/se	(10) PM b/se
Quartile ventilation: poor	-0.31 (0.21)	-0.30 (0.21)	-0.28 (0.20)	-0.32* (0.20)	-0.37* (0.19)					
Quartile ventilation: substantial	-0.48* (0.24)	-0.46* (0.25)	-0.59*** (0.21)	-0.53** (0.22)	-0.71*** (0.22)					
Quartile ventilation: full	-1.13*** (0.28)	-0.88*** (0.29)	-1.22*** (0.26)	-1.19*** (0.25)	-1.31*** (0.27)					
PC ventilation						-1.46*** (0.41)	-1.12*** (0.41)	-1.58*** (0.37)	-1.51*** (0.38)	-1.72*** (0.38)
Endline	-0.16 (0.13)	-0.20 (0.13)	-0.20 (0.13)	-0.18 (0.13)	0.12 (0.22)	-0.19 (0.14)	-0.22 (0.13)	-0.23* (0.13)	-0.20 (0.14)	-0.04 (0.23)
Volume=2		0.06 (0.18)					0.03 (0.19)			
Volume=3		-0.44 (0.35)					-0.53 (0.37)			
Volume=4		-0.61 (0.50)					-0.57 (0.49)			
Share of cooking events with measurement			0.27 (0.27)	0.45* (0.27)	0.55* (0.33)			0.17 (0.26)	0.38 (0.27)	0.50 (0.34)
IAP meter										
MicroPEM			0.91*** (0.22)	0.94*** (0.20)	0.94*** (0.19)			0.90*** (0.23)	0.95*** (0.21)	0.94*** (0.19)
Participant's age				-0.00 (0.01)	-0.00 (0.01)				-0.00 (0.01)	-0.00 (0.01)
Participant is homemaker				0.34* (0.19)	0.20 (0.18)				0.33* (0.18)	0.18 (0.17)
Participant is literate				0.46** (0.21)	0.43** (0.17)				0.50*** (0.22)	0.48*** (0.18)
HH is primarily Wolof (d)				0.03 (0.22)	0.01 (0.21)				0.01 (0.22)	0.01 (0.21)
HH size (#)				0.05** (0.02)	0.03 (0.03)				0.04* (0.02)	0.03 (0.02)
HH has a private tap (d)				0.20 (0.18)	0.26 (0.17)				0.22 (0.18)	0.29* (0.17)
HH has modern electricity (d)				0.08 (0.30)	-0.01 (0.29)				0.08 (0.32)	0.03 (0.31)
HH's normalized wealth index				-0.00 (0.13)	0.04 (0.12)				0.05 (0.12)	0.10 (0.10)
Traditional stove										
Basic metal stove					0.38 (0.42)					0.29 (0.39)
Improved woodfuel stove					-0.11 (0.30)					-0.17 (0.30)
LPG stove					-1.43*** (0.48)					-1.45*** (0.48)
Share of cooking on OFS					0.18 (0.28)					0.12 (0.30)
Total cooking duration					-0.00 (0.00)					-0.00 (0.00)
Tissue					0.00 (.)					0.00 (.)
Simple treatment stove					0.07 (0.30)					0.22 (0.33)
Advanced treatment stove					-0.01 (0.27)					0.16 (0.28)
Person-caterings per day					0.01** (0.00)					0.01** (0.00)

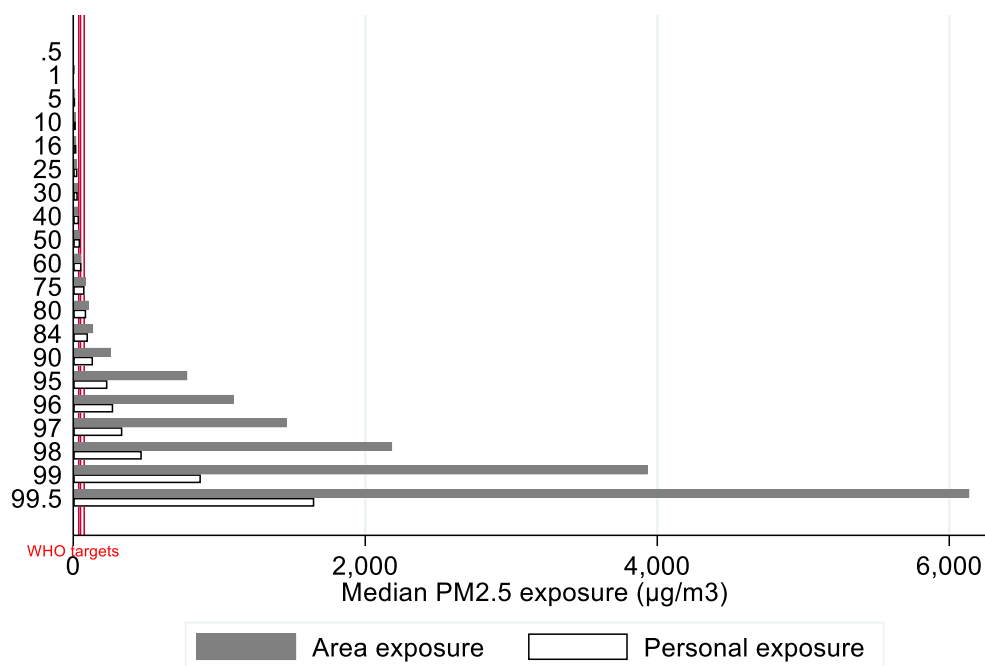
...

Table 3D.1 continued

Burn agricultural waste at home (d)					-0.18					-0.29*
					(0.14)					(0.15)
Participant avoids kitchen smoke					0.01					0.09
					(0.22)					(0.22)
Smell neighbors' smoke weekly (d)					0.50***					0.46***
					(0.15)					(0.15)
Constant	6.07***	6.04***	5.21***	3.76***	3.72***	6.20***	6.11***	5.45***	3.95***	3.93***
	(0.30)	(0.30)	(0.40)	(0.61)	(0.67)	(0.38)	(0.37)	(0.46)	(0.59)	(0.67)
Community and year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	220	220	219	212	211	220	220	219	212	211
Mean(Y) ref cat.	640.5	640.5	6.004	654.8	654.8
R-squared	0.211	0.229	0.298	0.378	0.463	0.195	0.214	0.279	0.361	0.446
delta										8.70

Note: ***, **, * denote statistical significance at the 1, 5 and 10% level respectively. The dependent variable is log of 24-hour average PM_{2.5} exposure. Standard errors are clustered at the household level and displayed in parentheses. The reference category of all variables of interest is their lowest category, i.e., most closed/smallest kitchen

Figure 3D.1: Median kitchen pollution and pollution exposure (PM_{2.5}), by percentiles



Note: The 95th percentile values states, for example, that during 95 percent of the day or 22.8 hours, pollution is below that value.

Table 3D.2: Ventilation and kitchen pollution (PM_{2.5}): single ventilation indicators

	(1) PM b/se	(2) PM b/se	(3) PM b/se	(4) PM b/se	(5) PM b/se	(6) PM b/se	(7) PM b/se	(8) PM b/se	(9) PM b/se	(10) PM b/se	(11) PM b/se	(12) PM b/se	(13) PM b/se	(14) PM b/se	(15) PM b/se
Open air: full	-0.99*** (0.33)	-0.63* (0.33)	-1.03*** (0.33)	-0.97*** (0.33)	-1.07*** (0.34)										
Walls: none															
Walls: poor						-0.21 (0.20)	-0.21 (0.20)	-0.18 (0.17)	-0.22 (0.19)	-0.21 (0.18)					
Walls: substantial						-0.58*** (0.21)	-0.59*** (0.21)	-0.64*** (0.22)	-0.57*** (0.20)	-0.48** (0.21)					
Walls: full						-1.24*** (0.35)	-0.93** (0.36)	-1.28*** (0.34)	-1.23*** (0.33)	-1.39*** (0.35)					
Roof: none															
Roof: poor											-0.30 (0.25)	-0.28 (0.25)	-0.35 (0.23)	-0.35 (0.25)	-0.48** (0.24)
Roof: substantial											-0.46 (0.30)	-0.46 (0.31)	-0.56** (0.26)	-0.55** (0.27)	-0.74*** (0.27)
Roof: full											-1.10*** (0.32)	-0.75** (0.30)	-1.19*** (0.31)	-0.97*** (0.33)	-1.18*** (0.32)
Endline	-0.20 (0.14)	-0.23* (0.13)	-0.24* (0.14)	-0.14 (0.14)	-0.12 (0.22)	-0.19 (0.13)	-0.21 (0.13)	-0.24* (0.13)	-0.14 (0.14)	-0.04 (0.23)	-0.22 (0.13)	-0.24* (0.13)	-0.25* (0.13)	-0.16 (0.14)	-0.00 (0.23)
Volume=2		0.07 (0.20)					0.09 (0.19)					0.05 (0.19)			
Volume=3		-0.46 (0.33)					-0.51 (0.35)					-0.32 (0.36)			
Volume=4		-0.58 (0.53)					-0.48 (0.52)					-0.74 (0.45)			
Constant	5.46*** (0.29)	5.51*** (0.30)	4.69*** (0.45)	3.18*** (0.63)	3.00*** (0.72)	5.79*** (0.27)	5.84*** (0.27)	4.95*** (0.42)	3.46*** (0.65)	3.25*** (0.73)	5.86*** (0.35)	5.90*** (0.36)	5.04*** (0.43)	3.31*** (0.59)	3.25*** (0.67)
Community and year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Measurement	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Cook and household	No	No	No	Yes	Yes	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Cooking behavior	No	No	No	No	Yes	No	No	No	No	Yes	No	No	No	No	Yes
N	220	220	219	212	211	220	220	219	212	211	220	220	219	212	211
Mean(Y) ref cat.	261.5	261.5	4.817	240.9	240.9	582.7	582.7	5.953	586.9	586.9	637.8	637.8	5.848	641.7	641.7
R-squared	0.182	0.196	0.258	0.371	0.446	0.207	0.221	0.288	0.396	0.473	0.194	0.212	0.278	0.369	0.454
delta					16.63										

Note: ***, **, * denote statistical significance at the 1, 5 and 10% level respectively. The dependent variable is log of 24-hour average PM_{2.5} exposure. Standard errors are clustered at the household level and displayed in parentheses. The reference category of all variables of interest is their lowest category, i.e., most closed/smallest kitchen.

Table 3D.3: Kitchen volume and kitchen pollution (PM_{2.5}), reduced sample and continuous volume specification

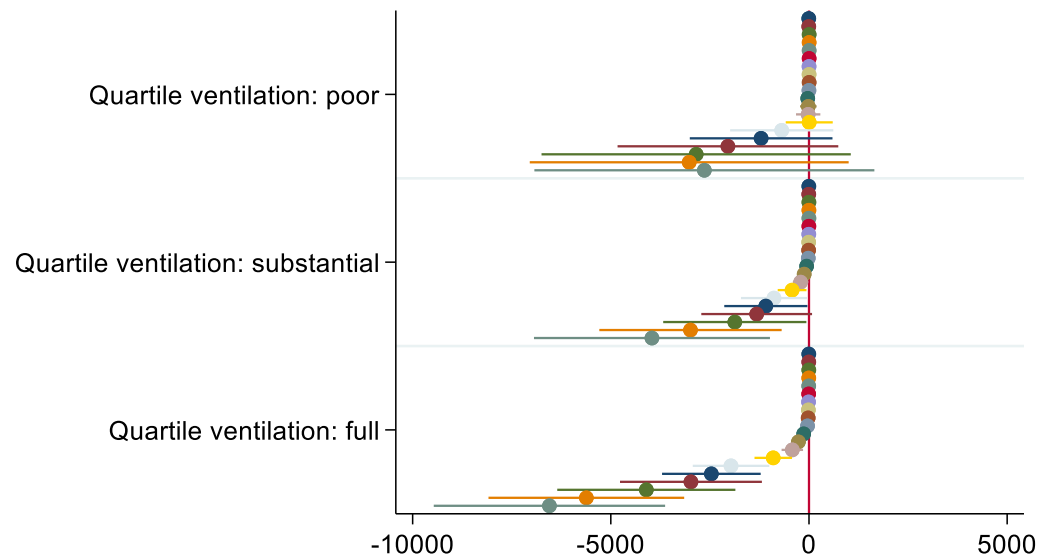
	(1) PM b/se	(2) PM b/se	(3) PM b/se	(4) PM b/se	(5) PM b/se
Kitchen volume (#)	-0.01 (0.01)	-0.00 (0.00)	-0.01* (0.00)	-0.01 (0.00)	-0.01 (0.01)
Quartile ventilation: poor					-0.30 (0.19)
Quartile ventilation: substantial					-0.64*** (0.22)
Quartile ventilation: full					-0.83*** (0.25)
Endline	-0.29** (0.14)	-0.33** (0.14)	-0.29** (0.14)	-0.14 (0.23)	0.03 (0.23)
Constant	5.43*** (0.33)	4.69*** (0.43)	3.39*** (0.55)	3.06*** (0.62)	3.69*** (0.65)
Community and year	Yes	Yes	Yes	Yes	Yes
Measurement	No	Yes	Yes	Yes	Yes
Cook and household	No	No	Yes	Yes	Yes
Cooking behavior	No	No	No	Yes	Yes
N	202	201	194	193	193
R-squared	0.178	0.258	0.355	0.428	0.478

*Note: ***, **, * denote statistical significance at the 1, 5 and 10% level respectively. The dependent variable is log of 24-hour average PM_{2.5} exposure. Standard errors are clustered at the household level and displayed in parentheses. The reference category of all variables of interest is their lowest category, i.e., most closed/smallest kitchen.*

Figure 3D.2: Ventilation and 5th – 95.5th percentile kitchen pollution (PM_{2.5})

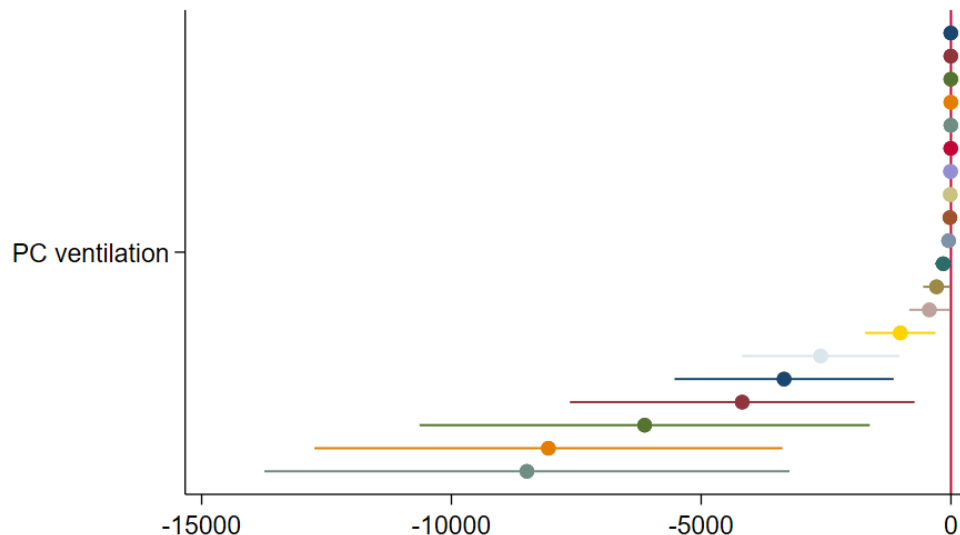
For this analysis of pollution percentiles, I abstain from log-transforming the outcome of interest, i.e., PM_{2.5} pollution, since distances between individuals across percentiles might vary. Reducing these distances by log-transformation would make differences in coefficients across percentiles difficult to interpret.

Panel A: Quartile Ventilation



Note: The reference category is their lowest category, i.e., unventilated kitchen; Number of obs.=135. I show the effect on absolute PM kitchen pollution and 95 CI. The percentiles range from 5th – 95.5th and are ordered from low (top) to high (bottom). The 95th percentile values states, for example, that during 95 percent of the day or 22.8 hours, pollution is below that value.

Panel B: PC Ventilation



Note: The reference category is their lowest category, i.e., unventilated kitchen; Number of obs.=135. I show the effect on absolute PM kitchen pollution and 95 CI. The percentiles range from 5th – 95.5th and are ordered from low (top) to high (bottom). The 95th percentile values states, for example, that during 95 percent of the day or 22.8 hours, pollution is below that value.

Table 3D.4: Ventilation and kitchen pollution (PM_{2.5}), with health covariates

	(1) PM b/se	(2) PM b/se	(3) PM b/se	(4) PM b/se	(5) PM b/se
Quartile ventilation: poor	-0.51*** (0.18)				
Quartile ventilation: substantial	-0.69*** (0.21)				
Quartile ventilation: full	-1.26*** (0.26)				
PC ventilation					-1.65*** (0.38)
Open air=0					
Open air: full		-1.07*** (0.34)			
Walls: poor					
Walls: poor			-0.21 (0.18)		
Walls: substantial			-0.48** (0.21)		
Walls: full			-1.39*** (0.35)		
Roof: poor					
Roof: poor				-0.48** (0.24)	
Roof: substantial				-0.74*** (0.27)	
Roof: full				-1.18*** (0.32)	
Participant has normal blood pressure	0.17 (0.15)	0.16 (0.16)	0.15 (0.16)	0.19 (0.16)	0.13 (0.17)
Participant has red eyes sometimes or more	0.43** (0.18)	0.38** (0.16)	0.41** (0.16)	0.31* (0.18)	0.42** (0.16)
Endline	0.10 (0.23)	-0.12 (0.22)	-0.04 (0.23)	-0.00 (0.23)	-0.03 (0.24)
Constant	3.53*** (0.70)	3.00*** (0.72)	3.25*** (0.73)	3.25*** (0.67)	3.78*** (0.70)
Community and year	Yes	Yes	Yes	Yes	Yes
Measurement	Yes	Yes	Yes	Yes	Yes
Cook and household	Yes	Yes	Yes	Yes	Yes
Cooking behavior	Yes	Yes	Yes	Yes	Yes
N	211	211	211	211	211
Mean(Y) ref cat.	654.8	240.9	586.9	641.7	.
R-squared	0.482	0.446	0.473	0.454	0.464

Note: ***, **, * denote statistical significance at the 1, 5 and 10% level respectively. The dependent variable is log of 24-hour average PM_{2.5} exposure. Standard errors are clustered at the household level and displayed in parentheses. The reference category of all variables of interest is their lowest category, i.e., most closed/smallest kitchen. Note that kitchen volume is not included in last specification due to its high multicollinearity with kitchen ventilation.

Table 3D.5: Ventilation and kitchen pollution (PM_{2.5}), reduced sample

	(1) PM b/se	(2) PM b/se	(3) PM b/se	(4) PM b/se	(5) PM b/se	(6) PM b/se	(7) PM b/se	(8) PM b/se	(9) PM b/se	(10) PM b/se
Quartile ventilation: poor	-0.31	-0.29	-0.26	-0.29	-0.32*					
	(0.21)	(0.21)	(0.20)	(0.20)	(0.19)					
Quartile ventilation: substantial	-0.45*	-0.44*	-0.55**	-0.47**	-0.66***					
	(0.25)	(0.26)	(0.22)	(0.22)	(0.21)					
Quartile ventilation: full	-0.83***	-0.85***	-0.90***	-0.72***	-0.88***					
	(0.29)	(0.31)	(0.27)	(0.24)	(0.26)					
PC ventilation						-1.05**	-1.10**	-1.23***	-0.95**	-1.25***
						(0.50)	(0.48)	(0.43)	(0.42)	(0.41)
Endline	-0.28**	-0.28*	-0.32**	-0.28**	-0.02	-0.30**	-0.29**	-0.34**	-0.30**	-0.14
	(0.14)	(0.14)	(0.13)	(0.14)	(0.23)	(0.14)	(0.15)	(0.14)	(0.15)	(0.23)
Volume=2		-0.01					-0.05			
		(0.19)					(0.20)			
Volume=3		-0.46					-0.54			
		(0.35)					(0.38)			
Volume=4		0.10					-0.09			
		(0.35)					(0.32)			
Constant	5.95***	6.00***	5.02***	3.53***	3.53***	5.95***	6.03***	5.15***	3.52***	3.52***
	(0.34)	(0.35)	(0.44)	(0.55)	(0.66)	(0.43)	(0.43)	(0.49)	(0.57)	(0.66)
Community and year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Measurement	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Cook and household	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Cooking behavior	No	No	No	No	Yes	No	No	No	No	Yes
N	193	193	192	186	185	193	193	192	186	185
Mean(Y) ref cat.	640.5	640.5	6.004	654.8	654.8
R-squared	0.205	0.213	0.306	0.387	0.492	0.183	0.195	0.282	0.370	0.467

Note: ***, **, * denote statistical significance at the 1, 5 and 10% level respectively. The dependent variable is log of 24-hour average PM_{2.5} kitchen pollution. Standard errors are clustered at the household level and displayed in parentheses. The reference category of all variables of interest is their lowest category, i.e., most closed/smallest kitchen.

Appendix 3E: Women's pollution exposure

Table 3E.1: Correlates of behavioral smoke avoidance

	(1) Never opens windows b/se	(2) Never opens windows b/se	(3) Never opens windows b/se	(4) Never avoids smoke b/se	(5) Never avoids smoke b/se	(6) Never avoids smoke b/se
Quartile ventilation: poor	0.38 (0.47)			0.07 (0.40)		
Quartile ventilation: substantial	1.01* (0.53)			0.25 (0.39)		
Quartile ventilation: full	3.08*** (1.07)			0.25 (0.42)		
Walls: poor		-0.17 (0.40)			0.39 (0.32)	
Walls: substantial					-0.04 (0.43)	
Walls: full		2.09* (1.10)			0.37 (0.47)	
Roof: poor			0.44 (0.57)			0.16 (0.42)
Roof: substantial			1.14** (0.57)			0.35 (0.41)
Roof: full			3.03** (1.28)			0.44 (0.41)
Endline	-2.06*** (0.57)	-2.00*** (0.58)	-2.09*** (0.54)	0.36 (0.38)	0.40 (0.38)	0.34 (0.39)
Participant's age	-0.02 (0.02)	-0.02 (0.02)	-0.03 (0.02)	-0.00 (0.01)	-0.00 (0.01)	-0.00 (0.01)
Participant is homemaker	-0.25 (0.40)	-0.23 (0.41)	-0.23 (0.41)	-0.30 (0.26)	-0.32 (0.26)	-0.29 (0.26)
Participant is literate	0.34 (0.51)	0.22 (0.50)	0.15 (0.51)	-0.05 (0.32)	-0.06 (0.33)	-0.07 (0.32)
HH is primarily Wolof (d)	1.64*** (0.48)	1.39*** (0.46)	1.75*** (0.50)	0.57 (0.43)	0.63 (0.43)	0.58 (0.42)
HH size (#)	-0.03 (0.04)	-0.03 (0.04)	-0.02 (0.03)	0.03 (0.02)	0.03 (0.02)	0.03 (0.02)
HH has a private tap (d)	-0.06 (0.44)	-0.05 (0.45)	-0.13 (0.42)	0.08 (0.33)	0.05 (0.34)	0.06 (0.33)
HH has modern electricity (d)	-0.28 (0.52)	-0.34 (0.53)	-0.25 (0.52)	0.64 (0.45)	0.64 (0.46)	0.67 (0.46)
HH's normalized wealth index	0.13 (0.26)	0.03 (0.24)	0.05 (0.26)	-0.14 (0.19)	-0.15 (0.18)	-0.13 (0.19)
Traditional stove						
Basic metal stove	1.49 (1.00)	0.97 (1.10)	1.71 (1.06)	0.85 (0.54)	0.91 (0.56)	0.87 (0.54)
Improved woodfuel stove	-0.04 (0.62)	0.02 (0.60)	-0.22 (0.62)	0.50 (0.59)	0.52 (0.61)	0.47 (0.59)
LPG stove	0.16 (0.90)	-0.20 (0.93)	0.14 (0.87)	1.35*** (0.50)	1.41*** (0.51)	1.37*** (0.50)
Share of cooking on OFS	-0.34 (0.60)	-0.26 (0.59)	-0.49 (0.61)	0.20 (0.48)	0.23 (0.49)	0.19 (0.48)
Tissue						
Simple treatment stove	0.12 (0.58)	0.20 (0.60)	0.24 (0.55)	-0.61 (0.56)	-0.64 (0.56)	-0.58 (0.57)
		...				

Table 3E.1 continued

	(1) Never opens windows b/se	(2) Never opens windows b/se	(3) Never opens windows b/se	(4) Never avoids smoke b/se	(5) Never avoids smoke b/se	(6) Never avoids smoke b/se
Advanced treatment stove	0.43 (0.63)	0.53 (0.60)	0.61 (0.61)	-0.38 (0.53)	-0.42 (0.53)	-0.37 (0.53)
Person-caterings per day	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.00 (0.01)	-0.00 (0.01)	-0.00 (0.01)
Smell neighbors' smoke weekly (d)	-0.78 (0.49)	-0.70 (0.46)	-0.65 (0.45)	0.25 (0.34)	0.25 (0.34)	0.25 (0.35)
Constant	2.94** (1.42)	2.91** (1.48)	2.96** (1.38)	-2.29** (1.11)	-2.27** (1.12)	-2.36** (1.11)
N	358	306	358	396	396	396
R-squared						

Table 3E.2: Ventilation and pollution exposure (PM_{2.5}): composite ventilation indicators

	(1) PM b/se	(2) PM b/se	(3) PM b/se	(4) PM b/se	(5) PM b/se	(6) PM b/se	(7) PM b/se	(8) PM b/se	(9) PM b/se	(10) PM b/se
Quartile ventilation: poor										
Quartile ventilation: poor	-0.08 (0.09)	-0.10 (0.09)	-0.11 (0.09)	-0.12 (0.09)	-0.13 (0.09)					
Quartile ventilation: substantial	-0.10 (0.08)	-0.12 (0.08)	-0.11 (0.07)	-0.11 (0.08)	-0.14* (0.08)					
Quartile ventilation: full	-0.08 (0.08)	0.07 (0.11)	-0.06 (0.08)	-0.05 (0.08)	-0.08 (0.08)					
PC ventilation						-0.16 (0.12)	-0.00 (0.17)	-0.12 (0.11)	-0.08 (0.11)	-0.09 (0.12)
Endline	-0.16** (0.06)	-0.16*** (0.06)	-0.21*** (0.06)	-0.21*** (0.06)	-0.11 (0.07)	-0.16** (0.06)	-0.16*** (0.06)	-0.22*** (0.06)	-0.21*** (0.06)	-0.11 (0.07)
Volume=2		-0.06 (0.07)					-0.06 (0.07)			
Volume=3		0.11 (0.11)					0.08 (0.11)			
Volume=4		-0.32*** (0.11)					-0.21* (0.12)			
Primary cook			0.47*** (0.07)	0.47*** (0.07)	0.50*** (0.07)			0.48*** (0.07)	0.47*** (0.07)	0.50*** (0.07)
Secondary cook			0.09 (0.08)	0.06 (0.09)	0.08 (0.09)			0.10 (0.08)	0.07 (0.08)	0.09 (0.09)
Main cooks (#)			-0.02 (0.04)	-0.03 (0.04)	-0.05 (0.04)			-0.01 (0.04)	-0.03 (0.04)	-0.04 (0.04)
PE daytime wearing compliance (#)			0.00*** (0.00)	0.01*** (0.00)	0.00*** (0.00)			0.00*** (0.00)	0.01*** (0.00)	0.00*** (0.00)
Participant's age				-0.01** (0.00)	-0.00* (0.00)				-0.00* (0.00)	-0.00* (0.00)
Participant is homemaker				-0.03 (0.06)	-0.05 (0.06)				-0.03 (0.06)	-0.04 (0.06)
Participant is literate				0.07 (0.08)	0.06 (0.08)				0.07 (0.08)	0.06 (0.08)
HH is primarily Wolof (d)				-0.08 (0.08)	-0.07 (0.08)				-0.07 (0.07)	-0.05 (0.08)
HH size (#)				0.01* (0.00)	0.00 (0.01)				0.01 (0.00)	0.00 (0.01)
HH has a private tap (d)				-0.07 (0.07)	-0.05 (0.07)				-0.06 (0.07)	-0.04 (0.07)

...

Table 3E.2 continued

	(1) PM b/se	(2) PM b/se	(3) PM b/se	(4) PM b/se	(5) PM b/se	(6) PM b/se	(7) PM b/se	(8) PM b/se	(9) PM b/se	(10) PM b/se
HH has modern electricity (d)				0.13 (0.10)	0.10 (0.10)				0.14 (0.10)	0.10 (0.10)
HH's normalized wealth index				-0.02 (0.04)	-0.01 (0.05)				-0.01 (0.04)	-0.00 (0.04)
Traditional stove										
Basic metal stove					-0.07 (0.09)					-0.07 (0.09)
Improved woodfuel stove					-0.09 (0.10)					-0.09 (0.10)
LPG stove					-0.07 (0.11)					-0.05 (0.11)
Share of cooking on OFS					0.10 (0.09)					0.09 (0.08)
Total cooking duration					0.00 (0.00)					0.00 (0.00)
Tissue										
Simple treatment stove					-0.07 (0.11)					-0.07 (0.11)
Advanced treatment stove					0.01 (0.09)					0.01 (0.09)
Person-caterings per day					0.00 (0.00)					0.00 (0.00)
Burn agricultural waste at home (d)					0.03 (0.06)					0.03 (0.06)
Participant avoids kitchen smoke					0.01 (0.07)					0.01 (0.07)
Smell neighbors' smoke weekly (d)					0.07 (0.06)					0.06 (0.06)
Constant	4.88*** (0.18)	4.89*** (0.18)	4.25*** (0.18)	4.25*** (0.23)	4.15*** (0.26)	4.91*** (0.19)	4.86*** (0.20)	4.25*** (0.19)	4.22*** (0.23)	4.12*** (0.27)
Community and year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	418	418	418	415	414	418	418	418	415	414
Mean(Y) ref cat.	142.9	142.9	4.759	143.1	143.1
R-squared	0.101	0.118	0.219	0.243	0.262	0.100	0.109	0.215	0.238	0.256

*Note: ***, **, * denote statistical significance at the 1, 5 and 10% level respectively. The dependent variable is log of 24-hour average PM_{2.5} exposure. Standard errors are clustered at the household level and displayed in parentheses. The reference category of all variables of interest is their lowest category, i.e., most closed/smallest kitchen.*

Table 3E.3: Ventilation and pollution exposure (PM_{2.5}): single ventilation indicators

	(1) PM b/se	(2) PM b/se	(3) PM b/se	(4) PM b/se	(5) PM b/se	(6) PM b/se	(7) PM b/se	(8) PM b/se	(9) PM b/se	(10) PM b/se	(11) PM b/se	(12) PM b/se	(13) PM b/se	(14) PM b/se	(15) PM b/se	(16) PM b/se	(17) PM b/se	(18) PM b/se	(19) PM b/se	(20) PM b/se
Open air=0																				
Open air: poor	-0.13 (0.09)	0.12 (0.20)	-0.09 (0.09)	-0.06 (0.09)	-0.05 (0.09)															
Walls: poor																				
Walls: poor						-0.09 (0.06)	-0.10 (0.06)	-0.12* (0.06)	-0.12* (0.07)	-0.14** (0.07)										
Walls: substantial						-0.10 (0.08)	-0.10 (0.08)	-0.07 (0.08)	-0.09 (0.08)	-0.12 (0.08)										
Walls: full						-0.15 (0.10)	0.20 (0.22)	-0.10 (0.09)	-0.07 (0.09)	-0.07 (0.10)										
Roof: poor																				
Roof: poor										-0.07 (0.11)	-0.07 (0.10)	-0.07 (0.10)	-0.06 (0.10)	-0.08 (0.10)						
Roof: substantial										-0.03 (0.09)	-0.04 (0.09)	-0.05 (0.09)	-0.05 (0.09)	-0.09 (0.09)						
Roof: full										-0.08 (0.10)	0.05 (0.12)	-0.08 (0.09)	-0.05 (0.09)	-0.08 (0.09)						
Location=Inside																				
Location=Attached																0.30** (0.15)	0.31** (0.15)	0.33** (0.13)	0.32** (0.13)	0.30** (0.13)
Location=Separated																0.07 (0.08)	0.07 (0.08)	0.09 (0.09)	0.10 (0.09)	0.08 (0.09)
Location=Open air																-0.05 (0.11)	0.61* (0.32)	-0.01 (0.12)	0.02 (0.12)	-0.00 (0.12)

...

Table 3E.3 continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
	PM	PM	PM	PM	PM	PM	PM	PM	PM	PM	PM	PM	PM	PM	PM	PM	PM	PM	PM	PM
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Endline	-0.16**	-0.16***	-0.22***	-0.21***	-0.11	-0.16**	-0.16***	-0.22***	-0.21***	-0.12	-0.16***	-0.16**	-0.22***	-0.21***	-0.11	-0.16**	-0.17***	-0.22***	-0.21***	-0.12
	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.08)	(0.06)	(0.06)	(0.06)	(0.06)	(0.08)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)
Volume=2		-0.06					-0.08					-0.07					-0.07			
		(0.07)					(0.07)					(0.07)					(0.07)			
Volume=3		0.09					0.09					0.06					0.09			
		(0.11)					(0.11)					(0.11)					(0.10)			
Volume=4		-0.32					-0.45**					-0.27**					-0.73**			
		(0.21)					(0.22)					(0.11)					(0.32)			
Constant	4.84***	4.85***	4.20***	4.19***	4.07***	4.89***	4.91***	4.26***	4.26***	4.16***	4.86***	4.88***	4.24***	4.22***	4.13***	4.74***	4.77***	4.06***	4.06***	3.98***
	(0.16)	(0.16)	(0.18)	(0.22)	(0.26)	(0.17)	(0.17)	(0.18)	(0.23)	(0.26)	(0.18)	(0.18)	(0.19)	(0.22)	(0.25)	(0.18)	(0.18)	(0.20)	(0.24)	(0.27)
Community and year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Measurement	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Cook and household	No	No	No	Yes	Yes	No	No	No	Yes	Yes	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Cooking behavior	No	No	No	No	Yes	No	No	No	No	Yes	No	No	No	No	Yes	No	No	No	No	Yes
N	418	418	418	415	414	418	418	418	415	414	418	418	418	415	414	417	417	417	414	413
Mean(Y) ref cat.	123.6	123.6	4.637	123.6	123.6	146.2	146.2	4.787	146.4	146.4	129.6	129.6	4.689	129.7	129.7	103.2	103.2	4.560	103.2	103.2
R-squared	0.101	0.110	0.215	0.238	0.255	0.104	0.118	0.220	0.243	0.263	0.0990	0.112	0.215	0.238	0.257	0.110	0.125	0.226	0.248	0.265

Note: ***, **, * denote statistical significance at the 1, 5 and 10% level respectively. The dependent variable is log of 24-hour average PM_{2.5} exposure. Standard errors are clustered at the household level and displayed in parentheses. The reference category of all variables of interest is their lowest category, i.e., most closed/smallest kitchen.

Table 3E.4: Ventilation and pollution exposure (PM_{2.5}), with health covariates

	(1) PM b/se	(2) PM b/se	(3) PM b/se	(4) PM b/se	(5) PM b/se	(6) PM b/se
Quartile ventilation: poor						
Quartile ventilation: poor	-0.14 (0.09)					
Quartile ventilation: substantial	-0.14* (0.08)					
Quartile ventilation: full	-0.08 (0.09)					
PC ventilation					-0.09 (0.12)	
Open air=0						
Open air: full		-0.04 (0.09)				
Walls: poor						
Walls: poor			-0.14** (0.07)			
Walls: substantial			-0.12 (0.08)			
Walls: full			-0.07 (0.10)			
Roof: poor						
Roof: poor				-0.08 (0.10)		
Roof: substantial				-0.09 (0.09)		
Roof: full				-0.08 (0.09)		
Location=Inside						
Location=Attached						0.31** (0.13)
Location=Separated						0.08 (0.09)
Location=Open air						-0.00 (0.12)
Participant has normal blood pressure	0.04 (0.06)	0.03 (0.06)	0.04 (0.06)	0.03 (0.06)	0.03 (0.06)	0.02 (0.06)
Participant has red eyes sometimes or more	0.00 (0.08)	-0.00 (0.07)	0.01 (0.08)	-0.01 (0.07)	-0.01 (0.07)	-0.02 (0.07)
Endline	-0.11 (0.08)	-0.12 (0.08)	-0.12 (0.08)	-0.12 (0.08)	-0.12 (0.08)	-0.12 (0.08)
Constant	4.14*** (0.26)	4.06*** (0.26)	4.14*** (0.26)	4.12*** (0.26)	4.11*** (0.27)	3.97*** (0.28)
Community and year	Yes	Yes	Yes	Yes	Yes	Yes
Measurement	Yes	Yes	Yes	Yes	Yes	Yes
Cook and household	Yes	Yes	Yes	Yes	Yes	Yes
Cooking behavior	Yes	Yes	Yes	Yes	Yes	Yes
N	414	414	414	414	414	413
Mean(Y) ref cat.	143.1	123.6	146.4	129.7	.	103.2
R-squared	0.263	0.256	0.263	0.258	0.256	0.265

Note: ***, **, * denote statistical significance at the 1, 5 and 10% level respectively. The dependent variable is log of 24-hour average PM_{2.5} exposure. Standard errors are clustered at the household level and displayed in parentheses. The reference category of all variables of interest is their lowest category, i.e., most closed/smallest kitchen. Note that kitchen volume is not included in last specification due to its high multicollinearity with kitchen ventilation (especially for open air cooking households)