Experimental Evidence on the Economics of Rural Electrification

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We present results from an experiment that randomized the expansion of electric grid infrastructure in rural Kenya. Electricity distribution is a canonical example of a natural monopoly. Experimental variation in the number of connections, combined with administrative cost data, reveals considerable scale economies, as hypothesized. Randomized price offers indicate that demand for connections falls sharply with price. Among newly connected households, average electricity consumption is very low, implying low consumer surplus. We do not find meaningful medium-run impacts on economic and noneconomic outcomes. We discuss implications for current efforts to increase rural electrification in Kenya and highlight how various factors may affect interpretation.

This research was supported by the Berkeley Energy and Climate Institute, the Blum Center for Developing Economies, the Center for Effective Global Action, the Development Impact Lab (USAID [US Agency for International Development] cooperative agreements AID-OAA-A-13-00002 and AIDOAA-A-12-00011, part of the USAID Higher Education Solutions Network), the International Growth Centre, the University of California Center for Energy and Environmental Economics, the Weiss Family Program Fund for Research in Development Economics, the World Bank DIME (Development Impact Evaluation) i2i

Electronically published March 4, 2020
[*Journal of Political Economy*, 2020, vol. 128, no. 4]
 0022-3808/2020/12804-0009$10.00

I. Introduction

Investments in infrastructure—including transportation, water and sanitation, telecommunications, and electricity systems—are primary targets for international development assistance. In 2018, for example, the World Bank directed a third of its global lending portfolio to infrastructure.[1] The basic economics of these investments—which tend to involve high fixed costs, relatively low marginal costs, and long investment horizons—can justify government investment, ownership, and subsequent regulation. While development economists have begun to measure the economic impacts of various types of infrastructure, including transportation (Faber 2014; Donaldson 2018), water and sanitation (Devoto et al. 2012; Patil et al. 2014), telecommunications (Jensen 2007; Aker 2010; Björkegren 2019), and electricity systems (Dinkelman 2011; Lipscomb, Mobarak, and Barham 2013; Burlig and Preonas 2016; Chakravorty, Emerick, and Ravago 2016; Barron and Torero 2017), there remains limited empirical evidence that links the demand-side and supply-side economics of infrastructure investments, in part because of methodological challenges. For instance, often it is difficult not only to identify exogenous sources of variation in the presence of infrastructure but also to obtain relevant administrative-cost data on infrastructure projects.

In this paper, we analyze the economics of rural electrification. We present experimental evidence on both the demand side and the supply side of electrification, specifically, household connections to the electric grid. We compare demand and cost curves and evaluate medium-run impacts on a range of economic, health, and educational outcomes to better understand the economics of mass rural electrification.

The study setting is 150 rural communities in Kenya, a country where grid coverage is rapidly expanding. In partnership with Kenya's Rural Electrification Authority (REA), we provided randomly selected clusters

(Impact Evaluation to Development Impact) Fund, and an anonymous donor. We thank Francis Meyo, Susanna Berkouwer, Victor Bwire, Elisa Cascardi, Corinne Cooper, Stephen Harrell, Eric Hsu, Radhika Kannan, Anna Kasimatis, Tomas Monárrez, Emma Smith, Felipe Vial, and Catherine Wright for excellent research assistance, as well as colleagues at Innovations for Poverty Action Kenya and Remit Kenya. This research would not have been possible without our partners at the REA and Kenya Power. Hunt Allcott, David Atkin, Severin Borenstein, Raj Chetty, Carson Christiano, Maureen Cropper, Aluma Dembo, Esther Duflo, Garance Genicot, Sébastien Houde, Kelsey Jack, Marc Jeuland, Asim Khwaja, Mushfiq Mobarak, Samson Ondiek, Billy Pizer, Matthew Podolsky, Javier Rosa, Mark Rosenzweig, Manisha Shah, Jay Taneja, Duncan Thomas, Chris Timmins, Liam Wren-Lewis, and many seminar participants provided helpful comments. We are also grateful to the editor, Michael Greenstone, and four anonymous referees for extremely useful suggestions. All errors remain our own. Data are provided as supplementary material online.

[1] In 2016 and 2017, the World Bank allocated over 40% of total lending toward its Energy and Extractives, Transportation, Information and Communications Technologies, and Water, Sanitation, and Waste Management sectors (World Bank 2018).

of households an opportunity to connect to the grid at subsidized prices. The intervention generated exogenous variation both in the price of a grid connection and in the scale of each local construction project. As a result, we can estimate the demand curve for grid connections among households and, in a methodological innovation of this study, the average and marginal cost curves associated with household grid-connection projects of varying sizes. We then exploit the exogenous variation in grid connections induced by the randomized subsidy offers to estimate electrification impacts.

Household demand for grid connections is lower than predicted, even at high subsidy rates. For example, lowering the connection price by 57% (relative to the prevailing price) increases demand by less than 25 percentage points. The cost of supplying connections, however, is high, even at universal community coverage, where the gains from economies of scale are attained. In our preferred specification using revealed-preference data, estimated consumer surplus from grid connections is roughly one-fifth of total construction costs. We derive a second measure of consumer surplus from a grid connection based on the subsequent benefits derived from consuming electricity, and this measure similarly implies low consumer surplus. In addition, we do not find economically meaningful or statistically significant impacts of electrification across a range of economic and noneconomic (e.g., health, education) outcomes, collected in two rounds of surveys conducted roughly 16 and 32 months after connection.

We next discuss several caveats in interpreting these results. First, the experiment generated a temporary reduction in the price of a grid connection. If credit-constrained households valued grid electricity services but were not able to raise the funds required to complete the purchase, the demand curve would underestimate the willingness to pay and thus consumer surplus. We present ancillary analyses from stated-preference data on the potential importance of credit constraints in this context. We also consider the roles of bureaucratic red tape and low grid reliability in reducing demand and of leakage in increasing construction costs.

Electricity systems serve as canonical examples of natural monopolies in microeconomics textbooks. Empirical estimates in the literature date back to Christensen and Greene (1976), who examine economies of scale in electricity generation. In recent decades, initiatives to restructure electricity markets around the world have been motivated by the view that while economies of scale are limited in generation, the transmission and distribution of electricity continue to exhibit standard characteristics of natural monopolies (Joskow 2000).

We differentiate between two separate components of electricity distribution. First, there is an access component, which consists of physically extending and connecting households to the grid and is the subject of this paper. Second, there is a service component, which consists of the ongoing provision of electricity. There is some evidence of economies of scale in both areas. Engineering studies show how the costs of grid extension may vary, depending on settlement patterns (Zvoleff et al. 2009), or can be reduced through the application of spatial electricity planning models (Parshall et al. 2009). With regard to electricity services, data from municipal utilities have been used to demonstrate increasing returns to scale in maintenance and billing (Yatchew 2000). Although recent work has examined the demand for rural electrification using both survey data (Abdullah and Jeanty 2011) and experimental variation (Bernard and Torero 2015; Barron and Torero 2017), this is the first study, to our knowledge, that combines experimental estimates on the demand for and costs of grid connections as well as the medium-run economic and noneconomic impacts of grid connections. By combining these elements, we contribute to ongoing debates regarding the economics of rural electrification in low-income regions.

In sub-Saharan Africa, roughly 600 million people currently live without electricity (IEA 2014), and achieving universal access to modern energy has become a primary goal for policy makers, nongovernmental organizations, and international donors. In 2013, the United States launched a multibillion-dollar aid initiative, Power Africa, with a goal of adding 60 million new connections in Africa. The United Nations Sustainable Development Goals include “access to affordable, reliable, sustainable and modern energy for all.” In Kenya, the government has recently invested heavily in expanding the electric grid to rural areas, and even though the rural household electrification rate remains relatively low, most households are now “under grid,” or within connecting distance of a low-voltage line (Lee et al. 2016).[2] As a result, the “last-mile” grid connectivity we study has recently emerged as a political priority in Kenya.

At the macroeconomic level, there is a strong correlation between energy consumption and economic development, and it is widely agreed that a well-functioning energy sector is critical for sustained economic growth. There is less evidence, however, on how energy drives poverty reduction and how investments in industrial energy access compare to the economic and social impacts of electrifying households. For rural communities, there are also active debates about whether increased energy access should be driven mainly by grid connections or via distributed solutions, such as solar lanterns and solar home systems (Lee, Miguel, and Wolfram 2016).

Although we find that the estimated consumer surplus from household grid connections is less than the total connection cost, universal access to

[2] In 2014, the rural electrification rate in Kenya was 12.6%, according to the World Bank DataBank (http://data.worldbank.org).

electricity may still conceivably increase social surplus.[3] For example, mass electrification may transform rural life in several ways: with electricity, individuals may be exposed to more media and information; they might participate more actively in public life and generate improvements in the political system or public policy; and children could study more and be more likely to obtain work outside of rural subsistence agriculture later in life. However, roughly 16 and 32 months after being connected to the grid, rural Kenyan households show little evidence of any such gains or their precursors. For instance, there are no meaningful impacts on objective political knowledge among respondents or on child test score performance. Of course, it is possible that the impacts of electrification take longer to materialize. Further long-run impact studies will thus be useful.

The remainder of this paper is organized as follows. Section II presents several natural monopoly scenarios that are empirically tested; section III discusses rural electrification in Kenya; section IV describes the experimental design; section V presents the main empirical findings; section VI offers an interpretation of these results, focusing on institutional and implementation challenges to rural electrification and their implications; and section VII concludes.

II. Theoretical Framework

In the classic definition, an industry is a natural monopoly if the production of a particular good or service by a single firm minimizes cost (Viscusi, Harrington, and Vernon 2005). More advanced treatments elaborate on the concept of subadditive costs, which extends the definition to multiproduct firms (Baumol 1977). Textbook treatments point out that real-world examples involve physical distribution networks and specifically cite water, telecommunications, and electric power (Samuelson and Nordhaus 1998; Carlton and Perloff 2005; Mankiw 2011).

A. Standard Model

We consider the case of an electric utility that provides communities of households with connections to the grid. To supply these connections, the utility incurs a fixed cost to build a low-voltage (LV) trunk network of poles and wires in each community. In the standard model, illustrated in figure 1*A*, the electricity distribution utility is a natural monopoly facing high fixed costs, constant or declining marginal costs, and a downward-sloping average-total-cost curve. As coverage increases, the marginal cost

[3] Note that we generally do not focus on “social welfare” because doing so would require imposing a particular social welfare function. Rather, we use the term “social surplus” throughout to capture the sum of consumer surplus from grid electrification, weighing all households equally, minus the costs of electrification.

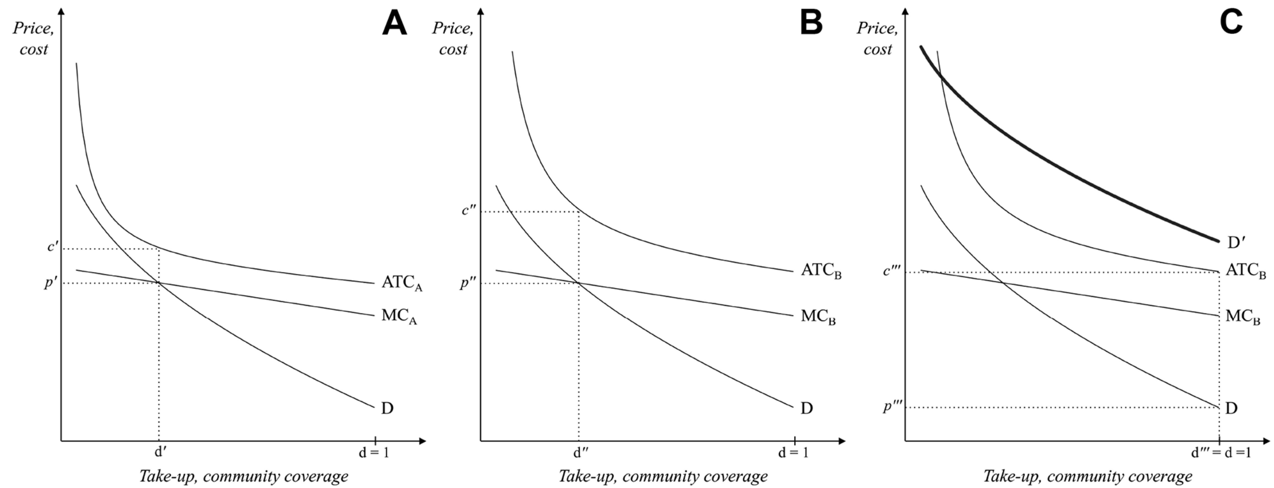

FIG. 1.—The electric utility as a natural monopoly. In *A*, the electric utility is a natural monopoly facing high fixed costs, decreasing marginal costs (MC_A), and decreasing average total costs (ATC_A). MC_A intersects demand (*D*) at d'. At d', a government-subsidized mass electrification program would increase social surplus, since consumer surplus (i.e., the area under the demand curve) is greater than total cost. *B*, Alternative scenario with higher fixed costs. In this case, consumer surplus is less than total cost at all quantities. A mass electrification program would not increase social surplus unless there are, for instance, positive externalities from private grid connections. *C*, Scenario in which social demand (D') is sufficiently high for the ideal outcome to be full coverage, subsidized by the government.

of connecting an additional household should decrease, as the distance to the network declines. At high coverage levels, the marginal cost is essentially the cost of a drop-down service cable that connects a household to the LV network. Household demand for a grid connection reflects expectations about the difference between the consumer surplus from electricity consumption and the price of monthly electricity service.

The social planner's solution is to set the connection price equal to the level where the demand curve intersects the marginal cost curve (p' in the figure). As a result of the natural monopoly characteristics of the industry, the utility is unable to cover its costs at this price, and the social planner must subsidize the electric utility to make up the difference. In figure 1*A*, total consumer surplus from the electricity distribution system is positive at price p', since the area under the demand curve is greater than the total cost, represented by rectangle with height c' and width d'.

Note that we are assuming that, once connected, a household can purchase electricity at the social marginal cost. If this is true, there are no further social gains or losses from electricity consumption. An alternative approach to estimating the social surplus from a connection is to calculate the surplus from consuming electricity over the life of the connection. We implement this approach empirically in section V.E.[4]

B. Alternative Scenarios and Potential Externalities from Grid Connections

We illustrate an alternative scenario in figure 1*B*. Here, the natural monopolist faces higher fixed costs. In this case, consumer surplus (the area under curve *D*) is less than total cost at all quantities, and a subsidized electrification program reduces social surplus.

In figure 1*C*, we maintain the same demand and cost curves as in *B* but illustrate a case in which the social demand curve (D') lies above observed private demand (*D*). There may be positive externalities (spillovers) from private grid connections, especially in communities with strong social ties, where connected households share the benefits of power with neighbors. In rural Kenya, for instance, people may spend some time in the homes of neighbors who have electricity, watching TV, charging mobile phones, and enjoying better-quality lighting in the evening. Another factor that could contribute to a gap between *D* and D' is the possibility that households have higher intertemporal discount rates than policy makers. For example, if electrification allows children to study more and thus increases future earnings, there may be a gap if parents discount their children's future earnings more than the social planner. Further, observed

[4] Section I of app. A (apps. A–C are available online) provides an additional discussion of the underlying theoretical framework.

private demand may be low because of market failures, such as credit constraints or a lack of information about long-run private benefits; what we call the "social demand curve" would also reflect the willingness to pay for grid connections if these issues were resolved. In general, if D' lies above D, there may be a price at which the consumer surplus (the area under D') exceeds total costs. In the scenario depicted in figure 1*C*, D' is sufficiently high, and the ideal outcome is to offer full community coverage at price p''' and a subsidy equal to the rectangle with height $c''' - p'''$ and width d''' provided to the utility.

Which of these cases best fits the data? In this paper, we trace out the natural monopoly cost curves, using experimental variation in the connection price and in the scale of each local construction project, together with a combination of actual and estimated construction cost data provided by the electricity utility. The estimated cost curves correspond to the segments of figure 1 that range between the preexisting rural household electrification rate, which is roughly 5% at baseline in our data, and full community coverage ($d = 1$). This is the policy-relevant range for governments considering subsidized mass rural connection programs in communities where they have already installed distribution transformers.

One type of externality that we do not consider is the negative spillover from greater energy consumption because of higher CO_2 emissions and other forms of environmental pollution. These would shift the total social cost curve up, making mass electrification less desirable. In the next section, we discuss aspects of electricity generation in Kenya that make these issues less of a concern in the study setting than they often are elsewhere.

III. Rural Electrification in Kenya

Kenya has a relatively "green" electricity grid, with most energy generated through hydropower and geothermal plants and fossil fuels representing just one-third of total installed electricity generation capacity, which totaled 2,295 MW (megawatts) as of 2015. Installed capacity is projected to increase tenfold by the year 2031, with the proportion of electricity generated using fossil fuels remaining roughly the same over time.[5] Thus, Kenya appears poised to substantially increase rural energy access by relying largely on non-fossil-fuel energy sources.

In recent years, there has been a dramatic increase in the coverage of the electric grid. For instance, in 2003, a mere 285 public secondary schools

[5] Specifically, in 2015, total installed capacity consisted primarily of hydropower (36%), fossil-fuel (35%), and geothermal (26%) sources. Based on government planning reports (referred to as *Vision 2030*), total installed capacity is expected to reach 21,620 MW by 2031, with fossil fuels (e.g., diesel and natural gas) representing 32% of the total. Many other African countries generate similar shares of electricity from non-fossil-fuel sources (Lee, Miguel, and Wolfram 2016).

(3% of the total) across the country had electricity connections, while by November 2012, Kenyan newspapers projected that 100% of the country's 8,436 secondary schools would soon be connected. The driving force behind this push was the creation of the REA, a government agency established in 2007 to accelerate the pace of rural electrification. The REA's strategy has been to prioritize the connection of three major types of rural public facilities, namely, market centers, secondary schools, and health clinics. Under this approach, public facilities not only benefited from electricity but also served as community connection points, bringing previously off-grid homes and businesses within relatively close reach of the grid. In June 2014, the REA announced that 89% of the country's 23,167 identified public facilities had been electrified. This expansion had come at a substantial cost to the government, over $100 million per year. The national household electrification rate, however, remained relatively low at 32%, with far lower rates in rural areas.[6] Given this grid expansion, the Ministry of Energy and Petroleum identified last-mile connections for "under-grid" households as the most promising strategy to reach universal access to power.

During the decade leading up to the study period, any household in Kenya within 600 m of an electric transformer could apply for an electricity connection at a fixed price of $398 (35,000 KES [Kenya shillings]).[7] The fixed price had initially been set in 2004 and was intended to cover the cost of building infrastructure in rural areas. As the REA expanded grid coverage, the connection price emerged as a major public issue in 2012, appearing with regular frequency in national newspapers and policy discussions. The fixed price seemed out of reach for many, if not most, poor, rural households to afford (annual per capita income is below $1,000 for most rural households). However, Kenya Power, the national electricity utility, held firm, estimating the cost of supplying a single connection in a grid-covered area to be far higher, at $1,435. After the government rejected its proposal to increase the price to $796 (70,000 KES) in April 2013, Kenya Power initially announced that it would no longer supply grid connections in rural areas at all, limiting supply to households that were a single service cable away from an LV line. As a result, the government agreed to temporarily provide Kenya Power with subsidies to cover any excess costs incurred, allowing the expansion of rural grid connections

[6] The REA provided us with estimates of the proportion of public facilities electrified (June 2014), the national electrification rate (June 2014), and overall REA investments (between July 2012 and June 2015).

[7] All KES amounts are converted to US dollars (USD) at the 2014 average exchange rate of 87.94 KES/USD. All 2016 and 2017 KES amounts are first adjusted to 2014 levels, using the appropriate inflation rate, before being converted to USD. The fixed price of 35,000 KES was established in 2004 to reduce uncertainty surrounding cost-based pricing. Anecdotally, it was common for service providers to lower the cost-based price in exchange for a bribe.

to continue at the same \$398 price as before. In February 2014, the government ended these subsidies to Kenya Power, and it was again widely reported that the price would increase to \$796. Ultimately, the \$398 fixed price remained in place for households within 600 m of a transformer throughout the first phase of the study period, from late 2013 to early 2015, when study subsidies for electric grid connections were distributed and redeemed.

The government announced in May 2015 (after baseline data collection activities and redemption of most subsidy offers) that it had secured \$364 million—primarily from the African Development Bank and the World Bank—to launch the Last Mile Connectivity Project (LMCP), a subsidized mass electrification program that plans to eventually connect four million "under-grid" households and that, once launched, would lower the fixed connection price to \$171 (15,000 KES). This new price was based on the Ministry of Energy and Petroleum's internal predictions for take-up in rural areas and was revealed publicly in May 2015. The take-up data described in the next section were collected during the decade-long \$398 price regime and before any public announcement of the planned LMCP.

IV. Experimental Design and Data

A. *Sample Selection*

The field experiment took place in 150 "transformer communities" in Busia and Siaya, two counties that are typical of rural Kenya in terms of electrification and economic development and where population density is fairly high (see table B1). Each transformer community is defined as all households located within 600 m of a secondary electricity distribution (LV) transformer, the official distance threshold that Kenya Power used for connecting buildings at the standard price. The communities were sampled in cooperation with the REA.[8]

Between September and December 2013, teams of surveyors visited each of the 150 communities to conduct a census of the universe of households within 600 m of a central transformer. This database, consisting of 12,001 unconnected households in total, served as the study sampling frame and showed that 94.5% of households remained unconnected despite being "under grid" (Lee et al. 2016).

Although population density in this setting is fairly high, the average minimum distance between structures is 52.8 m.[9] These distances make illegal connections quite costly, since local pole infrastructure would be required to "tap" into nearby lines; in practice, the number of illegal

[8] See sec. II of app. A for further details and fig. B1 for a map of the sample communities.

[9] A map of a typical transformer community (in terms of residential density) illustrating the degree to which unconnected households are under grid is presented in fig. B2.

connections is negligible in the study sample (unlike in some urban areas in Kenya).

For each unconnected household, we calculated the shortest (straight-line) distance to an LV line, approximated by either a transformer or a connected structure. To limit construction costs, the REA requested that we limit the sampling frame to the 84.9% of households located within 600 m of a transformer that were also no more than 400 m away from an LV line.[10] Applying this threshold, we randomly selected 2,289 "under-grid" households, or roughly 15 households per community.

B. Experimental Design and Implementation

Between February and August 2014, a baseline survey was administered to the 2,289 main study households. We additionally collected baseline data for 215 already-connected households, or 30.5% of the universe of households observed to be connected to the grid at the time of the census, sampling up to four connected households in each community, wherever possible.[11]

In April 2014, we randomly divided the sample of transformer communities into treatment and control groups of equal size, stratifying the randomization process to ensure balance across county, market status, and whether the transformer installation was funded early on (namely, between 2008 and 2010). The 75 treatment communities were then randomly assigned into one of three subsidy-treatment arms of equal size. After baseline survey activities in each community, between May and August 2014, each treatment household received an official letter from the REA describing a time-limited opportunity to connect to the grid at a subsidized price.[12] Households were given 8 weeks to accept the offer and deposit an amount equal to the effective connection price (i.e., full price less the subsidy amount) into the REA's bank account.[13] The treatment and control groups are characterized as follows.

1. High-subsidy arm: 380 unconnected households in 25 communities are offered a \$398 (100%) subsidy, resulting in an effective price of \$0.

[10] In other words, all households located within 400 m of the transformer were included in the sampling frame, while some households located between 400 and 600 m of the transformer were excluded.

[11] A summary of the experimental design is provided in fig. B3.

[12] An example of this letter is provided in fig. B4.

[13] Note that in this setting, one does not need a bank account to deposit funds into a specified bank account. The high-subsidy (free-treatment) group described below is not subject to the additional ordeal of traveling to town to access a bank branch and interacting with bank staff to deposit funds into the REA's account. For households that need to pay for a connection, the total time and transport cost of such a trip is roughly a few hundred KES (or a few USD), far smaller than the experimental subsidy amounts.

2. Medium-subsidy arm: 379 unconnected households in 25 communities are offered a \$227 (57%) subsidy, resulting in an effective price of \$171.
3. Low-subsidy arm: 380 unconnected households in 25 communities are offered a \$114 (29%) subsidy, resulting in an effective price of \$284.
4. Control group: 1,150 unconnected households in 75 communities receive no subsidy and face the regular connection price of \$398 throughout the study period.

Treatment households also received an opportunity to install a basic, certified household wiring solution (a "ready-board") in their homes at no additional cost. Each ready-board—valued at roughly \$34 per unit—featured a single light bulb socket, two power outlets, and two miniature circuit breakers.[14] Each connected household was fitted with a prepaid electricity meter at no additional charge. At the end of the 8-week period, treatment households could once again connect to the grid at the standard connection price of \$398.

After verifying payments, we provided the REA with a list of households to be connected. This initiated a lengthy process to complete the design, contracting, construction, and metering of connections: the first household was metered in September 2014, the average connection time was 7 months, and the final household was metered over a year later, in December 2015.[15] Additional details are discussed in section VI.B.

Between May and November 2016, we administered a first follow-up survey ("R1") to 2,217 study households, or 96.9% of the baseline sample. We also surveyed an additional 1,328 households—between 6 and 11 households per community—as part of a "spillover sample," randomly sampling households that were observed to be unconnected at the time of the census but were not chosen for the baseline survey. Furthermore, we administered short language and math tests to all 12–15-year-olds in the sample, 2,302 children in total.

Between October and December 2017, we administered a second follow-up survey ("R2") to 2,151 study households, or 94.0% of the baseline

[14] The ready-board was designed and produced for the project by Power Technics, an electronic supplies manufacturer in Nairobi. A diagram of the ready-board is presented in fig. B5.

[15] In fig. B7, we present a time line of project milestones and grid connection–related news over the study period. Note that by late 2017, a small number of households began to be connected through the LMCP. In 2014, however, neither the sample households nor the research team anticipated such progress. For instance, before the intervention, there were concerns that the price would increase; during the intervention, 397 households provided a reason for why they declined a subsidized offer, and not one cited the possibility of a lower future price; and the LMCP price reduction was not publicly announced until May 2015, long after subsidy offers had expired. These patterns alleviate concerns that households were anticipating a general price reduction over the course of the experiment.

sample. In the R2 survey, we did not survey spillover-sample households and did not administer language and math tests. Instead, we collected test score data for 649 adolescents who would have been eligible to take the Kenya Certificate of Primary Education (KCPE) examination over the period of the study.

Following Casey, Glennerster, and Miguel (2012), we registered three preanalysis plans; these are available at https://doi.org/10.1257/rct.350-8.2 and in appendix C. Preanalysis plan A specifies the analyses of the demand and cost data, and preanalysis plans B and C specify the analyses of electrification impacts using the R1 and R2 survey data, respectively.

C. Data

The analysis combines a variety of survey, experimental, and administrative data collected and compiled between August 2013 and December 2017. The data sets include community characteristics data ($N = 150$), baseline household survey data ($N = 2{,}504$), experimental demand data ($N = 2{,}289$), administrative community construction cost data ($N = 77$), follow-up household survey data ($N = 5{,}696$), and children's test score data ($N = 2{,}589$).

D. Baseline Characteristics

Table 1 summarizes differences between unconnected and connected households at baseline. Connected households are characterized by higher living standards across almost all proxies for income.[16] They have higher-quality walls (of brick, cement, or stone rather than mud), have higher monthly basic energy expenditures, and own more land and assets, including livestock, household goods (e.g., furniture), and electrical appliances. Most unconnected households (92%) rely on kerosene as their primary lighting source, while only 6% and 3% of unconnected households own solar lanterns and solar home systems, respectively.

In table B2, we report baseline descriptive statistics and perform randomization checks. On average, 63% of respondents are female, just 14% have attended secondary school, and 66% are married. In terms of occupation, 77% are primarily farmers. These are overwhelmingly poor households, as evidenced by the fact that only 15% have high-quality walls.

[16] These patterns are consistent with the stated reasons for why households remain unconnected. In fig. B6, we show that, at baseline, 95.5% of households cited the high connection price as the primary barrier to connectivity. The second- and third-most-cited reasons—which were the high cost of wiring (10.2%) and the high monthly cost (3.6%), respectively—are also related to costs. Note that no households said that they were unconnected because they were waiting for a lower connection price or a government-subsidized rural electrification program.

TABLE 1
Differences between Unconnected and Grid-Connected Households at Baseline

	Unconnected (1)	Connected (2)	p-Value of Difference (3)
Sample size	2,289	215	
	A. Household Head (Respondent) Characteristics		
Female (%)	62.9	58.6	.22
Age (years)	52.3	55.8	<.01
Senior citizen (%)	27.5	32.6	.11
Attended secondary schooling (%)	13.3	45.1	<.01
Married (%)	66.0	76.7	<.01
Not a farmer (%)	22.5	39.5	<.01
Employed (%)	36.1	47.0	<.01
Basic political awareness (%)	11.4	36.7	<.01
Has bank account (%)	18.3	60.9	<.01
Monthly earnings (USD)	16.9	50.6	<.01
	B. Household Characteristics		
No. of members	5.2	5.3	.76
Youth members (age ≤ 18)	3.0	2.6	.01
High-quality walls (%)	16.0	80.0	<.01
Land (acres)	1.9	3.7	<.01
Distance to transformer (m)	356.5	350.9	.58
Monthly (noncharcoal) energy spending (USD)	5.5	15.4	<.01
	C. Household Assets		
Bednets	2.3	3.4	<.01
Sofa pieces	6.0	12.5	<.01
Chickens	7.0	14.3	<.01
Owns radio (%)	34.8	62.3	<.01
Owns television (%)	15.2	80.9	<.01

Note.—Columns 1 and 2 report sample means for households that were unconnected or connected at the time of the baseline survey. Column 3 reports the p-value of the difference between the means. The basic political awareness indicator captures whether the household head was able to correctly identify the presidents of Tanzania, Uganda, and the United States. Monthly earnings (USD) includes the respondent's profits from businesses and self-employment, salary and benefits from employment, and agricultural sales for the entire household. In the 2013 census of all unconnected households, just 5% of rural households were connected to the grid. In our sample of respondents, we oversampled the number of connected households.

Households have 5.3 members, on average. Households spend \$5.55 per month on (noncharcoal) energy sources, primarily kerosene.[17]

We test for balance across treatment arms by regressing baseline household and community characteristics on indicators for the three subsidy levels, and we conduct F-tests that all treatment coefficients equal zero.

[17] In June 2014, the standard electricity tariff for small households was roughly 2.8 cents/kWh (kilowatt-hour). Taking into consideration fixed charges and other adjustments, \$5.55 translates into roughly 32 kWh of electricity consumption, which is enough for basic lighting, television, and fan appliances each day of the month.

For the 23 household-level and two community-level variables analyzed, F-statistics are significant at 5% for only two variables, namely, a binary variable indicating whether the respondent could correctly identify the presidents of Tanzania, Uganda, and the United States (a measure of political awareness) and monthly (noncharcoal) energy spending, indicating that the randomization created largely comparable groups.

V. Results

A. *Estimating the Demand for Electricity Connections*

In figure 2, we plot the experimental results on the demand for grid connections. Take-up of a free grid connection offer is nearly universal, but demand falls sharply with price and is close to zero among the low-subsidy-treatment group, as well as in the control (no-subsidy) group. Figure 2*A* presents the experimental results and compares them to the government's "prior" on demand, namely, the Ministry of Energy and Petroleum's internal predictions for take-up in rural areas. The government demand curve—which we learned of in early 2015 via a government report—was developed independently of our project and served as justification for the planned LMCP price of \$171 (15,000 KES). A key finding is that, even at generous subsidy levels, actual take-up is significantly lower than predicted by the government (or by our team; see fig. B8).[18] In figures 2*B* and 2*C*, we show that households with high-quality walls and greater earnings in the past month, respectively, had higher take-up rates in the medium- and low-subsidy arms, suggesting that demand increases at higher incomes.

If we extrapolate the [1.3, 7.1] segment of the demand curve through the intercept, the area under the demand curve is just \$12,421.[19] Based on average community density of 84.7 households, this implies an average valuation of just \$147 per household.

We estimate the following regression equation:

$$y_{ic} = \alpha + \beta_1 T_c^{\mathrm{L}} + \beta_2 T_c^{\mathrm{M}} + \beta_3 T_c^{\mathrm{H}} + X_c'\gamma + X_{ic}'\lambda + \epsilon_{ic}, \tag{1}$$

where y_{ic} is an indicator variable reflecting the take-up decision for household i in transformer community c. The binary variables T_c^{L}, T_c^{M}, and T_c^{H} indicate whether community c was randomly assigned to the low-, medium-, or high-subsidy arm, respectively, and the coefficients β_1, β_2, and β_3

[18] The government report projected take-up in rural areas nationally, rather than in our study region alone, and this is one possible source of the discrepancy. Moreover, the government report does not clearly specify the time frame over which households would be asked to raise funds for a connection, somewhat complicating the comparison.

[19] In sec. V.C, we discuss alternative assumptions regarding demand in the unobserved [0, 1.3] domain.

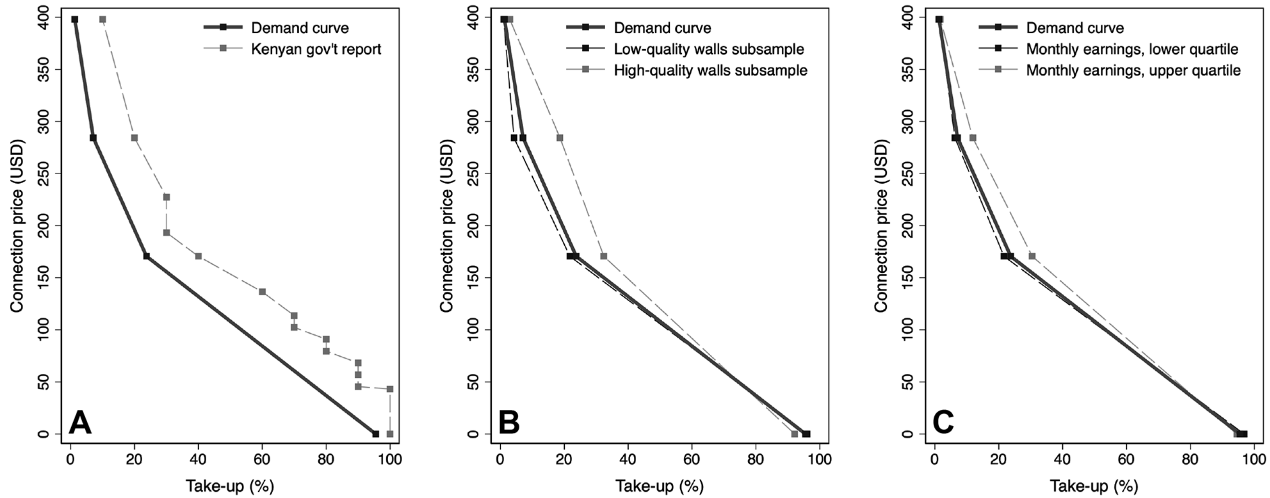

FIG. 2.—Experimental evidence on the demand for rural electrification. *A*, Comparison of the experimental results to the assumptions in an internal government report shared with our team in early 2015. *B*, Experimental results plotted separately for households with low- and high-quality walls. *C*, Results plotted separately for households in the lower and upper quartiles of monthly earnings, defined as the respondent's profits from businesses and self-employment, salary and benefits from employment, and agricultural sales for the entire household.

capture the subsidy impacts on take-up.[20] Following Bruhn and McKenzie (2009), we include a vector of community-level characteristics, X_c, containing variables used for stratification during randomization (see sec. IV.B). We also include a vector of baseline household-level characteristics, X_{ic}, containing prespecified covariates that may predict take-up (e.g., household size, chickens owned, respondent age, high-quality walls, and whether the respondent attended secondary school, is not a farmer, uses a bank account, engages in business or self-employment, or is a senior citizen). Standard errors are clustered by community, the unit of randomization.

Table 2 summarizes the results of estimating equation (1), where column 1 reports estimates from a model that includes only the treatment indicators and column 2 includes the household and community controls. All three subsidy levels lead to significant increases in take-up: the 100% subsidy increases the likelihood of take-up by roughly 95 percentage points, and the effects of the partial 57% and 29% subsidies are much smaller, at 23 and 6 percentage points, respectively. Columns 3–8 include interactions between the treatment indicators and household and community characteristics, which are listed in the column headings. Take-up in treatment communities is differentially higher in the low- and medium-subsidy arms for households with wealthier and more educated respondents; for instance, the coefficient on the interaction between secondary schooling and the medium subsidy indicator is 19.5%.[21]

From the findings in Bernard and Torero (2015), one might expect take-up to be higher in areas where grid connections are more prevalent if, as they argue, exposure to households with electricity leads individuals to better understand its benefits and value it more. Yet when we include an interaction with the baseline community electrification rate (col. 6) or an interaction with the proportion of neighboring households within 200 m connected to electricity at baseline (col. 7), we find no meaningful interaction effects.[22]

[20] We focus on this nonparametric specification after rejecting the null hypothesis that the treatment coefficients are linear in the subsidy amount (F-statistic = 23.03), a choice we specified in our preanalysis plan.

[21] In table B3, we compare the characteristics of households choosing to take up electricity across treatment arms. Households that paid more for an electricity connection (i.e., the low-subsidy arm) are wealthier on average than those who paid nothing (high-subsidy arm), i.e., they are better educated and more likely to have bank accounts, live in larger households with high-quality walls, spend more on energy, and have more assets. In tables B4A–B4E, we report all related demand regressions specified in our preanalysis plan, for completeness.

[22] Of course, this does not rule out the possibility of a differential effect at higher levels of electrification, since baseline household electrification rates are generally low in our sample of communities (the interquartile range is 1.8%–7.8%). Also, since community-level characteristics, such as income, are likely positively correlated across households, the lack of statistically significant coefficients may reflect the offsetting joint impacts of negative take-up spillovers and positively correlated take-up decisions; future research could usefully explore these issues.

TABLE 2
IMPACT OF GRID CONNECTION SUBSIDY ON TAKE-UP OF ELECTRICITY CONNECTIONS

			Interacted variable					
	(1)	(2)	High-Quality Walls (3)	Monthly Earnings (USD) (4)	Attended Secondary School (5)	Baseline Electrification Rate (6)	Baseline Neighbors Connected (7)	Report of Blackout in Past 3 Days (8)
T1. Low subsidy: 29% discount	5.8***	5.9***	3.6**	4.8***	4.5***	5.6**	4.8**	6.1**
	(1.4)	(1.5)	(1.5)	(1.5)	(1.4)	(2.2)	(1.9)	(2.6)
T2. Medium subsidy: 57% discount	22.4***	22.9***	21.3***	20.9***	19.8***	21.4***	21.4***	18.7***
	(4.0)	(4.0)	(4.4)	(4.1)	(3.8)	(6.2)	(3.5)	(5.1)
T3. High subsidy: 100% discount	94.2***	95.0***	95.6***	95.6***	95.2***	97.5***	96.1***	95.1***
	(1.2)	(1.3)	(1.2)	(1.3)	(1.3)	(1.7)	(1.3)	(2.4)
Interacted variable			.3	−.0	−1.0	.1	.1	−.9
			(1.4)	(.0)	(1.5)	(.1)	(.1)	(1.3)
T1 × interacted variable			12.3**	.1*	10.2	.1	.2	−.2
			(6.1)	(.0)	(7.0)	(.2)	(.2)	(3.1)
T2 × interacted variable			8.8	.1*	19.5***	.3	.3	7.6
			(7.8)	(.1)	(4.6)	(1.2)	(.2)	(7.8)

T3 × interacted variable			−5.5	−.0	−4.3	−.5*	−.2	−.2
			(3.9)	(.0)	(4.9)	(.3)	(.1)	(2.8)
Household and community controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,289	2,176	2,176	2,164	2,176	2,176	2,176	2,176
R^2	.68	.69	.69	.70	.70	.69	.69	.69

NOTE.—The dependent variable is an indicator variable (multiplied by 100) for household take-up, with a mean of 21.6. Take-up in the control group is 1.3. Robust standard errors clustered at the community level are in parentheses. Prespecified household controls include the age of the household head; indicators for whether the household respondent attended secondary school, is a senior citizen, is not primarily a farmer, is employed, and has a bank account; an indicator for whether the household has high-quality walls; and the number of chickens (a measure of assets) owned by the household. Prespecified community controls include indicators for the county, market status, whether the transformer was funded and installed early on (between 2008 and 2010), community electrification rate at baseline, and community population. Monthly earnings (USD) includes the respondent's profits from businesses and self-employment, salary and benefits from employment, and agricultural sales for the entire household. Interacted variables in cols. 7 and 8 are the proportion of neighbors (i.e., within 200 m) connected to electricity and an indicator for whether any households in the community reported a recent blackout, respectively.

* $p < .10$ (two-tailed).
** $p < .05$ (two-tailed).
*** $p < .01$ (two-tailed).

B. Estimating the Economies of Scale in Electricity Grid Extension

Across all projects in the sample, the average total cost per connection (ATC) is \$1,226. While this seems high, it is in line with several alternative estimates, including: (1) Kenya Power's public estimate of \$1,435 per rural connection, (2) the Ministry of Energy and Petroleum's estimate of \$1,602, and (3) a consultant's estimates of \$1,322 and \$1,601 in urban and rural areas, respectively (Korn 2014).[23]

An immediate consequence of the downward-sloping demand curve estimated above is that the randomized price offers generate exogenous variation in the number of households in a community that are connected as part of the same local construction project. This novel design feature allows us to experimentally assess the economies of scale in grid extension.

In our preferred approach to estimating ATC (Γ_c) as a function of the number of connections (M_c), we impose the following functional form, which features a community-wide fixed cost and linear marginal costs:

$$\Gamma_c = \frac{b_0}{M_c} + b_1 + b_2 M_c. \tag{2}$$

Imposing linear marginal costs both is economically intuitive (e.g., as community coverage increases, the marginal cost of connecting an additional household decreases) and closely matches the observed data. Regardless of the exact functional form, average costs decline in the number of households connected, as in the textbook natural monopoly case.[24]

The nonlinear estimation of equation (2) yields coefficient estimates (standard error) of $b_0 = 2{,}453.4$ (252.3) for the fixed cost, $b_1 = 999.4$ (138.8), and $b_2 = -3.2$ (3.6).[25] We take the derivative of the total cost

[23] Elsewhere, rural grid connection costs have been observed to be similar, ranging from \$1,100 per connection in Vietnam to \$2,300 per connection in Tanzania (Castellano et al. 2015). Note that in our setting, we cannot rule out that connecting a random group of households, rather than a contiguous set of households, may also have increased average cost estimates at low coverage levels.

[24] Note that our preferred nonlinear function differs from the quadratic function specified in our preanalysis plan. The quadratic function does not provide a good fit to the data: it predicts considerably lower costs at intermediate coverage levels while greatly overstating them at universal coverage. In retrospect, it was an oversight on our part to fail to consider the standard community-level fixed cost. See sec. III in app. A and figs. B9A and B9B for a more detailed discussion on estimating costs and comparisons of different ATC functional forms, respectively.

[25] In fig. 3, we estimate and plot ATC curves by combining two sets of cost data. First, for each community in which the project delivered an electricity connection ($n = 62$), we received budgeted costs for the number of poles and service lines, the length of LV lines, and design, labor, and transportation costs. We refer to these as "sample" data. Second, the REA provided us with budgeted costs for higher levels of coverage (i.e., at 60%, 80%, and 100% of the community connected) for a subset of the high-subsidy-arm communities ($n = 15$). We refer to these as "designed" data. The REA followed the same costing methodology for

function (which is obtained by multiplying eq. [2] by M_c) to estimate the linear marginal cost function:

$$MC_c = b_1 + 2b_2M_c = 999.4 - 6.5M_c. \quad (3)$$

For each community, we use the coefficient estimates to predict the ATC and marginal cost of connecting various levels of community coverage (Q)—defined as the proportion of initially unconnected households in the community that become connected, which takes on values from 0 to 100. In figure 3*A*, we compare the experimental demand curve with the ATC and marginal cost curves, plotted against Q.[26] Focusing on the ATC curve, we find evidence of strong initial economies of scale. However, the incremental cost savings appear to decline at higher levels of community coverage, and the estimates imply an average cost of approximately \$739 per connection at universal coverage ($Q = 100$).

In communities with larger populations, the higher density of households may potentially translate into a larger impact of scale on ATC. In figures B10A and B10B, we compare ATC curves across various subsamples of data. For instance, in figure B10A*A*, we compare ATC curves for communities with higher and lower populations and find the curves to lie nearly on top of each other. Although it appears that there are no significant effects of population on ATC in the range of densities observed in our sample, it seems plausible that ATC could be higher in other parts of Kenya with far lower residential density. In *B*, we compare ATC curves for communities with higher and lower land gradients and find that while the curves are similar, the average cost at universal coverage is somewhat higher for high-gradient communities (at \$839 per connection) than for low-gradient communities (at \$657 per connection).[27]

C. Experimental Approach to Estimating Social Surplus

In figure 3*B*, we estimate total cost and consumer surplus at full coverage. Note that we first focus on the revealed-preference demand estimates, and we return to discuss issues of credit constraints and informational asymmetries in section VI.

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both (e.g., the same personnel visited the field sites to design the LV network and estimate the costs), ensuring comparability between sample and designed communities. Combining the two sets of communities ($N = 77$) in the main analysis here enables us to trace out ATC across all coverage levels.

[26] Table B5 reports actual and predicted ATC values at various coverage levels.

[27] This result is consistent with that of Dinkelman (2011), which relies on a positive relationship between land gradient and ATC in South Africa to estimate the impacts of rural electrification on employment. See sec. III in app. A for a further discussion on the relationship between land gradient and costs.

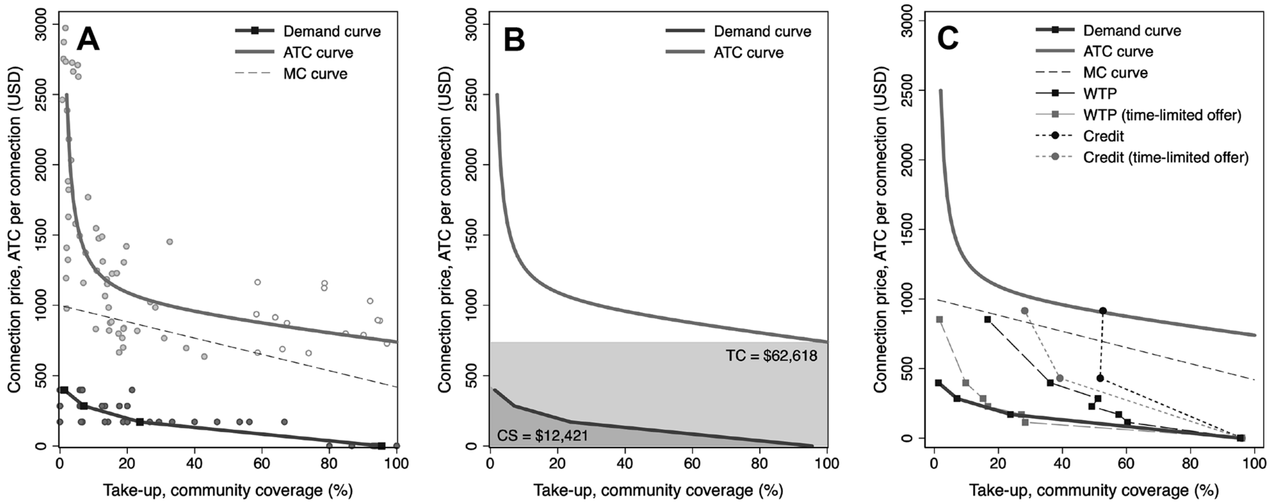

FIG. 3.—Experimental evidence on the social surplus implications of rural electrification. *A* combines the experimental demand curve with the population-weighted ATC curve corresponding to the predicted cost of connecting various population shares, based on the nonlinear estimation of ATC = $b_0/M + b_1 + b_2M$. Each point represents the community-level, budgeted estimate of ATC at a specific level of coverage. MC = marginal cost. *B* demonstrates that the estimated total cost of community electrification is \$62,618, based on average community density of 84.7 households. The area under the demand curve (consumer surplus [CS]) is estimated to be \$12,421. These estimates suggest that a mass electrification program would result in a social surplus loss of \$50,197 per community (i.e., \$593 per household). *C* combines the curves in *A* with the contingent-valuation (CV) questions included in the baseline survey. The CV questions included (1) whether the household would accept a hypothetical offer (i.e., at a randomly assigned price) to connect to the grid and (2) whether the household would accept the same offer if required to complete the payment in 6 weeks. The credit offer consisted of an up-front payment (ranging from \$39.80 to \$79.60), a monthly payment (ranging from \$11.84 to \$17.22), and a contract length (either 24 or 36 months). We plot the net present value of the credit offers, assuming a 15% discount rate. Additional details on the credit offers are provided in table B9.

The main observation is that the estimated demand curve for an electricity connection does not intersect the estimated marginal cost curve. To illustrate, at 100% coverage, we estimate the total cost of connecting a community to be $62,618, based on the mean community density of 84.7 households. In contrast, as noted in section V.A, consumer surplus at this coverage level is far less, at only $12,421, or less than one-quarter the costs. The estimated consumer surplus appears to be substantially smaller than total connection costs at all quantity levels, suggesting that rural household electrification may reduce social surplus. This result is robust to considering the uncertainty in the demand and cost estimates (see fig. B9C).

Specifically, our calculations suggest that a mass electrification program would result in a social surplus loss of $50,197 per community.[28] To justify such a program, discounted future social surplus gains of $593 would be required for each household in the community, above and beyond any economic or other benefits already considered by households in their own private take-up decisions. These social surplus gains could take several possible forms, including spillovers in consumption or broader economic production, an issue we explore below. Credit constraints or imperfect household information about the long-run benefits of electrification may both also contribute to lower demand, while negative pollution externalities could raise social costs.

In an alternative scenario, illustrated in figure B12, we estimate the demand for and costs of a program structured like the LMCP, which planned to offer a connection price of $171. In this case, only 23.7% of households would take up, based on the experimental estimates, and thus, unless the government were willing to provide additional subsidies or financing, the resulting electrification level would be low. At 23.7% coverage, there is an analogous social surplus loss of $18,809 per community, or $935 per connected household.

D. *Impacts of Rural Electrification*

Recent literature focuses on estimating the impacts of increasing access to electricity for rural households and communities. However, there is substantial variation in the types of outcomes examined, as well as the

[28] To calculate consumer surplus, we estimate the area under the unobserved [0, 1.3] domain by projecting the slope of the demand curve in the range [1.3, 7.1] through the intercept. The 1.3% figure is the proportion of the control group that chose to connect to the grid during the study period, which, for comparability to other points on the demand curve, we assume would happen over the same 8-week period as our offer. If anything, this assumption yields higher consumer surplus than alternative, perhaps more reasonable, assumptions on timing. Figure B11 considers the sensitivity of our results on social surplus loss to alternative demand curve assumptions. In panel *C* of that figure, the most conservative case, demand is a step function and intersects the vertical axis at $3,000. The social surplus loss is still $39,422 per community in this case.

magnitudes of impacts estimated.[29] Furthermore, nonexperimental studies typically face challenges in identifying credible exogenous sources of variation in electrification status. In contrast, we exploit experimental variation in grid electrification to test the hypothesis that households connected to the electricity grid enjoy improved living standards in the medium run, roughly 16 and 32 months after connection.

We limit our discussion of impacts to a set of prespecified outcomes that are meant to capture several important dimensions of energy access and overall living standards in the study setting.[30] In table 3, we report treatment effects on these outcomes, pooling together R1 and R2 data.[31] Because of relatively low take-up rates in the low- and medium-subsidy groups, we first limit the sample to include only a comparison between the high-subsidy group and the control group and estimate intention-to-treat (ITT) specifications. In column 2, we report the results of estimating the following regression for each outcome:

$$y_{icr} = \beta_0 + \beta_3 T_{Hc} + X_c'\Lambda + Z_{1icr}'\Gamma + s_r + \epsilon_{ic}, \quad (4)$$

where y_{icr} represents the primary outcome of interest for household i in community c in round r, T_{Hc} is a binary variable indicating whether community c was randomly assigned into the high-value-subsidy treatment, and s_r captures the survey-round fixed effect. As in equation (1), we include a vector of community-level characteristics, X_c, as well as a vector of prespecified, household-level characteristics, Z_{1icr}, and standard errors are clustered at the community level.

We then estimate treatment-on-treated (TOT) results, using data from all three subsidy-treatment groups. In column 3, we report the results of estimating the following equation:

$$y_{icr} = \beta_0 + \beta_1 E_{icr} + X_c'\Lambda_2 + Z_{1icr}'\Gamma_2 + s_r + \epsilon_{ic}, \quad (5)$$

where E_{icr} is a binary variable reflecting household i's electrification status in round r. We instrument for E_{icr} with the three indicator variables indicating whether community c was randomly assigned to the low-, medium-, or high-subsidy group.

Column 4 reports the false discovery rate (FDR)–adjusted q-values corresponding to the coefficient estimates in column 3, which limit the

[29] For example, some studies find that access to electricity increases measures of rural living standards, such as income and consumption (Khandker, Barnes, and Samad 2012; Khandker et al. 2014; van de Walle et al. 2015; Chakravorty, Emerick, and Ravago 2016), while others find no evidence of impacts on labor markets outcomes, assets, or housing characteristics (Burlig and Preonas 2016); see Lee, Miguel, and Wolfram (2020) for a discussion.

[30] See sec. III in app. A and preanalysis plans B and C for details on the construction of each variable.

[31] Individual survey-round results are provided in tables B6A and B6B.

expected proportion of rejections within a hypothesis that are Type I errors (i.e., false positives).[32]

Energy consumption increases in newly connected households, but overall consumption levels are low. The treatment effect on monthly electricity spending (table 3, outcome A2) is \$1.80–\$2.17, a miniscule amount corresponding to roughly 2–7 kWh of consumption per month. Although kerosene spending (B7) decreases by \$0.90–\$1.00, the effect on total energy spending (B8) is much smaller. While there are positive effects on the ownership of certain appliances, such as televisions (B5) and irons (B6), treated households only modestly expand the number of appliance types owned (B2), suggesting that newly connected households use power in limited ways.[33] The vast majority of households in the control group already own mobile phones (85.2%), most own radios (57.6%), and some even own televisions (21.3%).

By the follow-up surveys, there was a small increase in electrification at control households (to 12.2%), partly through the government LMCP in the study region, and a moderate increase in home solar-system ownership (to 14.1%). It is noteworthy that, despite the fact that there were major efforts to promote home solar systems in Kenya in this period and that these products are typically available on credit, relatively few control households elected to purchase a system; this may suggest that it is not just a lack of credit that reduces demand for electricity services.

Perhaps surprisingly, but consistent with the results in section V.B, we do not find evidence of widespread economic or noneconomic impacts. There are no detectable effects on asset ownership (table 3, outcome C4), consumption levels (C5), health outcomes (D1), or student test scores (D3, D4). There are moderate and statistically significant impacts on total hours worked (C3) and life satisfaction (D2), although only the latter is significant at the 5% level when multiple testing is adjusted for. The positive life-satisfaction effect could reflect a dimension of well-being that we fail to capture in our other primary outcomes, although it could also reflect social desirability bias among respondents. Another possibility is that life-satisfaction impacts are transitory, since the social status benefits of a grid connection would diminish as more community members are connected.

The overall effects are summarized in table 3, panel E, which combines the primary economic outcomes (from panel C) into a mean-effect economic index and the primary noneconomic outcomes (from panel D)

[32] As per our preanalysis plans, we follow the FDR approach of Anderson (2008) and Casey, Glennerster, and Miguel (2012).

[33] There are no meaningful impacts on the ownership of other appliance types beyond those presented in table 3.

TABLE 3

POOLED TREATMENT EFFECTS ON KEY OUTCOMES

	Control (1)	ITT (2)	TOT (3)	FDR q-value (4)
	A. Primary Energy Outcomes			
A1. Grid connected (%)	12.2	82.8***	. . .	. . .
	[32.7]	(1.8)		
A2. Monthly electricity spending (USD)	.33	1.80***	2.17***	. . .
	[1.36]	(.13)	(.14)	
	B. Additional Energy Outcomes			
B1. Electricity as main lighting source (%)	10.6	72.0***	86.8***	.001
	[30.8]	(2.1)	(2.1)	
B2. Number of appliance types owned	2.0	.3***	.4***	.002
	[1.4]	(.1)	(.1)	
B3. Owns mobile phone (%)	85.2	−2.4	−2.2	.246
	[35.5]	(1.5)	(1.8)	
B4. Owns radio (%)	57.6	4.6**	7.1***	.010
	[49.4]	(2.3)	(2.6)	
B5. Owns television (%)	21.3	9.3***	11.6***	.002
	[40.9]	(2.8)	(3.5)	
B6. Owns iron (%)	5.2	2.9**	3.8***	.010
	[22.2]	(1.2)	(1.4)	
B7. Monthly kerosene spending (USD)	2.64	−.90***	−1.00***	.001
	[2.75]	(.11)	(.13)	
B8. Monthly total energy spending (USD)	10.83	−.36	−.19	.870
	[21.83]	(.99)	(1.18)	
B9. Solar home system as main lighting source (%)	14.1	−13.0***	−16.1***	.001
	[34.8]	(1.2)	(1.3)	
	C. Primary Economic Outcomes			
C1. Household employed or own business (%)	36.0	2.9	2.2	.619
	[38.4]	(2.2)	(2.5)	
C2. Per capita monthly household earnings (USD)	12	−1	−2	.688
	[42]	(2)	(2)	
C3. Total hours worked last week	50.3	−2.6**	−3.5**	.095
	[24.4]	(1.2)	(1.5)	
C4. Total asset value (USD)	1,237	102	117	.457
	[1,110]	(76)	(93)	
C5. Per capita consumption of major items (USD)	185	−3	−4	.721
	[186]	(8)	(9)	
	D. Primary Noneconomic Outcomes			
D1. Recent health symptoms index	0	−.03	−.03	.721
	[1]	(.06)	(.07)	
D2. Normalized life satisfaction	0	.16***	.19***	.001
	[1]	(.04)	(.04)	
D3. Average student test Z-score	0	−.09	−.13	.457
	[1]	(.09)	(.10)	

TABLE 3 (*Continued*)

	Control (1)	ITT (2)	TOT (3)	FDR q-value (4)
D4. Average student KCPE test Z-score	0	−.12	−.17	.550
	[1]	(.13)	(.17)	
D5. Political and social awareness index	0	−.03	−.01	.861
	[1]	(.05)	(.05)	
D6. Perceptions of security index	0	.08	.13*	.303
	[1]	(.06)	(.08)	
	E. Mean Treatment Effects on Grouped Outcomes			
E1. Economic index (C outcomes)	0	.02	0	. . .
	[1]	(.06)	(.07)	
E2. Noneconomic index (D outcomes)	0	.01	0	. . .
	[1]	(.04)	(.05)	

NOTE.—Round 1 and 2 follow-up survey data are pooled together. Column 1 reports mean values in the control group, with standard deviations in brackets. Column 2 reports coefficients from separate ITT regressions in which the dependent variable (e.g., A1) is regressed on the high-subsidy-treatment indicator. The low- and medium-subsidy groups are excluded from these regressions. Sample sizes range from 1,419 to 2,894 for these regressions, except for the D3 and D4 regressions, which have sample sizes of 941 and 417, respectively. Column 3 reports coefficients from separate TOT (instrumental variable) regressions in which household electrification status is instrumented with the three subsidy-treatment indicators. Sample sizes range from 2,094 to 4,295 for these regressions, except for the D3 and D4 regressions, which have sample sizes of 1,411 and 644, respectively. All specifications include prespecified household, student, and community covariates, as well as a survey-round fixed effect. Column 4 reports the FDR-adjusted q-values associated with the coefficient estimates in col. 3. FDR-adjusted q-values are computed for each outcome within the additional energy outcomes group (panel B) and for each outcome within the primary outcomes group (panels C and D combined). In panel E, we report mean treatment effects on outcomes grouped into an economic and a noneconomic index. These groupings were not prespecified. Robust standard errors clustered at the community level are in parentheses. The D4 outcome is the average student Z-score on the Kenya Certificate of Primary Education (KCPE) test.

* $p < .10$ (two-tailed).

** $p < .05$ (two-tailed).

*** $p < .01$ (two-tailed).

into a noneconomic index.[34] The average economic effect is small, at 0.02 (in standard deviation [SD] units), and reasonably precisely estimated (standard error [SE] = 0.06), and the average effect on the noneconomic variables is also small, at 0.01 (in SD units, with SE = 0.04).[35]

[34] Although these indices were not prespecified, they are useful in summarizing the overall results and providing additional statistical power.

[35] As shown in table B6C, we also do not find evidence of any economically meaningful or statistically significant spillover impacts to local households, although these null effects are not precisely estimated.

E. Alternative Approach to Estimating Consumer Surplus

Alternatively, we can estimate consumer surplus from grid connections using an application of Dubin and McFadden's (1984) discrete/continuous model, like Davis and Killian (2011) and Barreca et al. (2016). This approach allows us to simulate consumer surplus for different cases regarding both baseline consumption levels and long-run consumption growth, under certain assumptions on the functional form of consumer demand.

Households are assumed to make a joint decision to acquire a grid connection and consume electricity, and consumer surplus from the connection is then measured as the discounted sum of surplus from consuming electricity over the life of the connection. We assume zero consumer surplus from electricity without a grid connection.[36] Consumer surplus measures depend on the level of monthly electricity consumption, the demand elasticity for electricity (i.e., the slope of the demand curve), the functional form of the demand curve, the long-run cost of supplying electricity, and the intertemporal discount rate.

This study's experimental variation in grid connection allows us to measure the shift in the demand curve for electricity directly on the basis of connected households' consumption levels. Lacking demand-elasticity estimates in Kenya, we use US estimates as a lower bound (e.g., Ito 2014) and report consumer surplus under a range of plausible assumptions. We assume linear demand (following Davis and Killian 2011 and Barreca et al. 2016) with elasticities evaluated at average consumption, a price equal to the constant long-run cost of electricity of \$0.12/kWh, and an annualized 15% discount rate.

Table 4 reports calculated consumer surplus across a range of demand-elasticity and consumption cases. In the study sample, mean monthly electricity consumption for newly connected households is 10.8 kWh in R2, an extremely small amount, as noted above. At 10 kWh per month (col. 1), consumer surplus ranges from \$98 to \$293 (depending on demand assumptions) and thus falls well below the average connection cost of \$1,226.[37] This result holds even if we assume that energy consumption grows at a rapid 10% per year (see col. 2); in this case, consumer surplus ranges from \$219 to \$658.

Rural connections appear to begin to yield positive social surplus at much higher levels of electricity consumption. Column 3 reports estimates at 70 kWh per month, roughly the mean R2 consumption level reported by

[36] Note that this will, if anything, lead us to overestimate the consumer surplus from acquiring a grid connection, since a subset of sample households receive electricity from solar home systems or car batteries.

[37] Note that consumer surplus at the lowest demand elasticity is similar to the average valuation obtained in the experiment, even though we arrive at these figures using two distinct methodologies.

TABLE 4
ALTERNATIVE APPROACH TO ESTIMATING CONSUMER SURPLUS PER HOUSEHOLD (HH)

	MONTHLY ELECTRICITY CONSUMPTION/BENCHMARK			
DEMAND ELASTICITY	10 kWh/Newly Connected HH (1)	10 kWh/ +10% Growth (2)	70 kWh/Baseline Connected HH (3)	190 kWh/ Nairobi HH (4)
−.45	98	219	684	1,857
−.30	147	329	1,026	2,786
−.15	293	658	2,053	5,572

NOTE.—Consumer surplus is estimated at various monthly electricity consumption levels and consumer demand elasticities. Assumptions include a 15% discount rate, a 30-year asset life, a $0.12/kWh price, linear demand, zero consumer surplus from electricity without a grid connection, and a 188-day connection delay. Mean consumption levels are 10.8 kWh for newly connected HHs in R2, 72.3 kWh for baseline connected HHs in R2, and 189.9 kWh for Nairobi HHs in 2014. See table B7 for additional benchmarks.

households already connected at baseline. Here, consumer surplus exceeds $400 (the private cost of a grid connection) and, at low elasticity, rises above the average connection cost in the experiment.[38] Column 4 reports estimates at 190 kWh per month, the mean consumption level in Nairobi.[39] At this level, consumer surplus ranges from $1,857 to $5,572.

VI. Interpretation

These results suggesting that rural electrification may reduce social surplus are perhaps surprising. Previous analyses have found substantial benefits from electrification (Dinkelman 2011; Lipscomb, Mobarak, and Barham 2013), though they have not directly compared benefits to costs. In the Philippines, Chakravorty, Emerick, and Ravago (2016) find that the physical cost of grid expansion is recovered after just a single year of realized expenditure gains. A World Bank report argues that household willingness to pay for electricity—which is calculated indirectly from kerosene-lighting expenditures—is likely to be well above the average supply cost in South Asia (World Bank 2008). Most of these studies, however, use nonexperimental variation or indirect measures of costs and benefits, and it is possible that they do not fully account for unobserved variables correlated with both electrification propensity and improved economic outcomes. In table 1, for example, we document a strong baseline correlation between household connectivity and living standards, and this pattern is consistent

[38] Note that a full accounting of social surplus for the fraction of households that were initially connected to the grid should include the costs of the transformer and medium-voltage network extensions. Including these would greatly increase the overall costs of rural electrification.

[39] In table B7, we present various benchmarks for monthly electricity consumption throughout Kenya.

with the possibility of meaningful omitted-variable bias in some nonexperimental studies.

In this section, we consider factors that could boost demand or drive down costs in our setting, affecting the interpretation and external validity of our results. Specifically, we present evidence on the role of credit constraints, bureaucratic red tape, and low grid reliability in reducing demand and the role of leakage in increasing costs, as well as possibly unaccounted-for spillovers.

A. *Short-Run Price Reduction and Credit Constraints*

Low demand may be driven in part by household credit constraints, which are well documented in low-income countries (de Mel, McKenzie, and Woodruff 2009; Karlan et al. 2014). In our context, concerns about the role of credit constraints may be exacerbated by the fact that we study a short-run subsidy offer for an electricity connection, redeemable over 8 weeks, rather than a permanent change in the connection price across villages (which would provide households with more time to raise the necessary funds); long-term differential prices across villages were not feasible in the study setting. This would reduce estimated demand and consumer surplus. On the other hand, short-run subsidies could have the opposite effect: absent credit constraints, temporarily low prices for durables could accelerate purchases from later periods, leading to higher measured willingness to pay (WTP; Hendel and Nevo 2006; Mian and Sufi 2012).

In figure 3*C*, we compare the experimental results to two sets of stated-WTP results obtained in the baseline survey to shed some light on the possible role of credit constraints. Stated WTP may better capture household valuation in the presence of credit constraints, although they may also overstate actual demand as a result of wishful thinking or social desirability bias (Hausman 2012).

Respondents were first asked whether they would accept a randomly assigned hypothetical price ranging from \$0 to \$853 for a grid connection.[40] Households were then asked whether they would accept the hypothetical offer if required to complete the payment in 6 weeks, a period chosen to be similar to the 8-week payment period in the experiment. We plot results in figure 3*C*, where the first curve (black squares) plots the results of the initial question and the second curve (gray squares) the follow-up question.

Stated demand is generally high,[41] and the demand curve falls dramatically when households are faced with a hypothetical time constraint,

[40] Each of \$114, \$171, \$227, \$284, and \$398 had a 16.7% chance of being drawn. Each of \$0 and \$853 had an 8.3% chance of being drawn. Nine households are excluded because of errors in administering the question.

[41] For more details on the stated demand for electricity connections, see table B8A, where we estimate the impact of the randomized offers on hypothetical and actual take-up,

suggesting that they are unable to pay (or borrow) the required funds on relatively short notice, an indication that credit constraints may be binding. At a price of $171, for example, stated demand is initially 57.6%, but it drops to 27.2% with the time constraint.

Although the experimental demand curve is substantially lower than the stated demand without time limits, it closely tracks the constrained stated demand: at $171, actual take-up in the experiment is 23.7%. The similarity between the constrained stated-demand and experimental results suggests that augmenting survey questions to incorporate realistic time frames and other contextual factors could help to elicit responses that more closely resemble revealed-preference behavior and are less prone to hypothetical bias (Murphy et al. 2005; Hausman 2012).

We also regressed a binary variable indicating whether a household first accepted the hypothetical offer without the time constraint but then declined the offer with the time constraint on a set of household covariates. Households with low-quality walls and respondents with no bank accounts are the most likely to switch their stated demand decision when faced with a pressing time constraint, consistent with the likely importance of credit constraints for these groups (see table B8C).[42]

In section V.C, we combined the estimated experimental demand and cost curves to show that rural electrification may reduce social surplus. The stated-preference results indicate that this outcome is likely to hold even if credit constraints were eased. For example, if we combine the cost curve with the stated demand for grid connections without time constraints, then households in the unobserved [0, 16.7] domain of the stated-demand curve (i.e., those willing to pay at least $853) must be willing to pay $2,920 on average for consumer surplus to be larger than total construction costs. While this cannot be ruled out, it appears unlikely in a rural setting where annual per capita income is below $1,000 for most households.[43]

Another way to address credit constraints is to offer financing plans for grid connections. In a second set of baseline stated-WTP questions, each household was randomly assigned a hypothetical credit offer consisting of an up-front payment (ranging from $39.80 to $127.93), a monthly payment (from $11.84 to $17.22), and a contract length (either 24 or 36 months); we present the results in figure 3*C*.[44] Households were first asked whether they would accept the offer (black circles) and then whether they would accept the offer if required to complete the up-front payment in 6 weeks

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and table B8B, which includes interactions between indicators for the hypothetical offers and key household covariates.

[42] Relatedly, see fig. B13 for a comparison of hypothetical demand curves for households with and without bank accounts and high-quality walls.

[43] The area under the stated-demand curve (without time constraints) is roughly $447 per household, under the assumption that the demand curve can be extended linearly in the [0, 16.7] range, intersecting the *y*-axis at $2,158.

[44] Results for a range of discount rates and net present values are presented in table B9.

(gray circles). We then plot take-up against the net present value of the credit offers based on an annualized 15% discount rate.

When households are offered financing, stated demand not only is high but also appears likely to be exaggerated, particularly when there are no time constraints to complete the up-front payments. For example, 52.7% of households stated that they would accept the $915.48 net-present-value offer, a package that consists of an up-front payment of $127.93 and monthly payments of $26.94 for 36 months. Eight weeks after accepting such an offer, a borrower will have paid $181, with an additional $915.92 due in the future. Yet stated demand for this option is twice as high as what we observe for the actual $171 8-week time-limited, all-in price offered to medium-subsidy-arm households in the experiment. Moreover, the fact that stated take-up is very similar across hypothetical contract offers with quite divergent net present values casts some doubt on the reliability of these stated-preference responses. Nonetheless, the area under the stated-demand curve in the case with financing and without time constraints is roughly $744 per household (under the same assumptions as above), which again falls short of average costs in our setting.

Figure 3*C*, combines the four stated-demand curves with the experimental demand and ATC curves. Visually, the only demand curves that appear to yield consumer surpluses that are potentially larger than total construction costs are the stated-demand curves for grid connections with credit offers, which, as we point out above, could be overstated.

Low demand may indicate that even with subsidies, grid connections are simply too expensive for many of the households in our poor rural setting. After the experiment, we asked households that were connected in the low- and medium-subsidy arms to name any sacrifices they had made to complete their payments: 29% of households stated that they had forgone purchases of basic household consumption goods, and 19% stated that they had not paid school fees. It seems likely that many households declined the subsidized offer because of binding budget constraints—in other words, poverty—rather than credit constraints alone.

With that said, the ITT results in table 3, column 2, suggest that medium-run impacts of electrification on economic (and other) outcomes are close to zero, even when credit constraints and budget constraints are eliminated by the high subsidy offer, which pushed the connection price to zero. This result implies that consumer surplus from grid connections is likely to be relatively low, unless credit constraints and budget constraints also play a role in limiting appliance purchases and monthly electricity consumption.

B. *Other Factors Contributing to Low Demand*

Low demand may also be partly attributable to the lengthy and bureaucratic process of obtaining an electricity connection. In the experiment, households waited a staggering 188 days, on average, after submitting their paperwork before they began receiving electricity. The delays were mainly caused by time lags in project design and contracting, as well as in the installation of meters.[45] The World Bank similarly estimates that in practice, it takes roughly 110 days to connect new business customers in Kenya (World Bank 2016).

Another major concern is the reliability of power. Electricity shortages and other forms of low grid reliability are well documented in less developed countries (Steinbuks and Foster 2010; Allcott, Collard-Wexler, and O'Connell 2016). In rural Kenya, households experience both short-term blackouts, which last for a few minutes up to several hours, and long-term blackouts, which can last for months and typically stem from technical problems with local transformers. The value a household places on a grid connection could be much lower when service is this unreliable.

During the 14-month period from September 2014 to December 2015 when households were being connected to the grid, we documented the frequency, duration, and primary reason for the long-term blackouts affecting sample communities. In total, 29 out of 150 transformers (19%) experienced at least one long-term blackout. On average, these blackouts lasted 4 months, with the longest lasting an entire year. During these periods, households and businesses did not receive any grid electricity. The most common reasons included transformer burnouts, technical failures, theft, and replaced equipment.[46] As a point of comparison, only 0.2% of transformers in California fail over a 5-year period, with the average blackout lasting a mere 5 hours.[47] That said, we find no strong statistical evidence that recent blackouts affect demand: in table 2, column 8, we include interactions between the treatment variables and an indicator for whether any household in the community reported a recent blackout (over the past 3 days) at baseline, and we find no statistically significant effects.

C. *Excess Costs from Leakage*

In table B11, we report the breakdown of budgeted versus invoiced electrification costs per community. The budgeted (ex ante) costs for each project are based on LV network drawings prepared by REA engineers.[48] The invoiced (ex post) costs are based on actual final invoices submitted by local contractors, detailing the contractor components of the labor,

[45] Field enumerators report that the electricity connection work may have sometimes been delayed because of expectations that bribes would be paid. See sec. IV in app. A for additional details.

[46] In table B10, we provide a list of all the communities that experienced long-term blackouts.

[47] Based on personal communications with Pacific Gas and Electric Company in December 2015.

[48] An example of an LV network drawing is provided in fig. B14.

transport, and materials that were required to complete each project. In total, it cost \$585,999 to build 101.6 km of LV lines to connect 478 households through the project.[49]

Overall, budgeted and invoiced costs per connection were nearly identical, amounting to \$1,201 and \$1,226, respectively. In other words, contractors submitted invoices that were only 1.7% higher than the budgeted amount, on average.[50] These cost figures reflect the reality of grid extension in rural Kenya. However, it is possible that they are higher than what would ideally be the case as a result of leakage and other inefficiencies that are common in low-income countries (Reinikka and Svensson 2004). In our context, leakage might occur during the contracting work, in the form of overreporting labor and transport, which may be hard to verify, and substandard construction quality (e.g., using fewer materials than required).[51]

To measure leakage, we sent teams of enumerators to each treatment community to count the number of electricity poles that were installed, and then we compared the actual number of poles to the poles included in the project designs and contractor invoices. While there is minimal variation between ex ante and ex post total costs, most contractors' projects showed large differences in the number of observed versus budgeted poles, with nearly all using fewer poles: the number of observed poles was 21.3% less than budgeted, a substantial discrepancy.[52]

Labor and transport costs may also reflect leakage. Labor is typically invoiced on the basis of the number of declared poles, and we show that these were inflated. Similarly, transport is invoiced on the basis of the declared mileage of vehicles carrying construction materials. In table B12, we analyze three highly detailed contractor invoices (for nine communities) that we obtained. These data contain evidence of overreported labor costs associated with the electricity poles, at 11.0% higher costs than expected, and overreported transport costs: based on a comparison between the reported mileage and the travel routes between the REA warehouse

[49] See sec. IV in app. A for an additional discussion.

[50] The similarity between planned and actual costs provides further confidence that the actual costs for the designed communities (at high coverage levels) would be reasonably accurate (see fig. 3).

[51] There is evidence of reallocations across subcategories in table B11, despite similar ex ante and ex post totals. Invoiced labor and transport costs, e.g., were 12.7% higher than the budgeted amounts, while invoiced local network costs were 6.5% lower.

[52] In fig. B15, we plot the discrepancies between costs and poles by contractor. In addition to being associated with missing public resources, if the planned number of poles reflects accepted engineering standards (i.e., poles are roughly 50 m apart, etc.), using fewer poles might lead to substandard service quality and even safety risks. For instance, local households may face greater injury risk because of sagging power lines between poles that are spaced too far apart, and the poles may be at greater risk of falling over. It is possible, however, that the REA's designs included extra poles, perhaps anticipating that contractors would not use them all.

and project sites (suggested by Google Maps), invoiced travel costs were 32.9% higher than expected.

Taken together, these findings indicate that electric grid construction costs may be substantially inflated because of mismanagement and corruption in Kenya, suggesting that improved contractor performance could reduce costs and possibly improve project quality and safety.[53] On the other hand, note that even with a 20%–30% reduction in construction costs, mass rural household electrification may still lead to a reduction in overall social surplus, based on the demand and cost estimates in figure 3 as well as the consumer surplus results in table 4.

D. *Factors That Increase Social Surplus from Rural Electrification*

The leading interpretation of our empirical findings is that mass rural household electrification does not lead to greater social surplus in Kenya, according to standard criteria. The cost of electrifying households appears to be five times higher than what households are willing and able to pay for these connections, and consumer surplus appears lower than total costs even when attempting to address credit constraints or utilizing subsequent electricity consumption patterns among connected households. While per-household costs fall sharply with coverage, reflecting the economies of scale in the creation of local grid infrastructure, they appear to remain higher than demand, implying that social surplus falls with each additional subsidized connection. These results are also consistent with the evidence of negligible medium-run economic, health, and educational impacts 16 and 32 months after connection. Further evidence of the low demand for electricity comes from a nearby area in Kenya, where just 1% of rural households provided with a large cash transfer of $1,000 chose to connect to the electric grid (Egger et al. 2019).

Yet it is plausible that these conclusions would change in settings with improved credit markets, better organizational performance by the electricity utility, or different levels of economic development. In table 5, we estimate the social surplus per household, using both the experimental approach presented in section V.C and the alternative demand approach in section V.E, under a range of assumptions about the underlying institutional and economic setting. In particular, we simulate the impact of "improving" the setting in five distinct ways: (1) allowing for household income growth of 3% per annum over 30 years (for the experimental approach; 1A) and electricity consumption growth of 10% per annum over

[53] To the extent that costs are high because contractors are overbilling the government, leakage may simply result in a transfer across Kenyan citizens and not a social surplus loss. The social welfare implications would depend on the relative weight the social planner places on contractors, taxpayers, and rural households.

TABLE 5
Predicting Social Surplus per Household under Different Assumptions

		Experimental approach		Alternative approach		
	C	CS	SS	CS	SS	Key Assumption(s)
Main estimates	739	147	−593	293	−446	
1A. Income growth (experimental approach)	...	+139		...		Growth of 3% per annum over 30 years (based on fig. 2*B*)
1B. Electricity consumption growth (alternative approach)		...		+365		Growth of 10% per annum over 30 years (see table 4, col. 2, row 3)
2. No credit constraints for grid connections	...	+301		...		Stated WTP without time constraints (see fig. 3*C*)
3. No transformer breakdowns	...	+33		+37		Reduce transformer breakdowns from 5.4% to 0% (see table B10)
4. No connection delays	...	+46		+52		Reduce waiting period from 188 to 0 days (see fig. A1)
5. No construction cost leakage	−157	...		...		Decrease total construction costs by 21.3% (see table B11)
Ideal scenario	582	665	83	747	166	

Note.—Main estimates of C (average connection cost), CS (consumer surplus), and SS (social surplus) correspond to fig. 3*B* (for the experimental approach) and table 4, col. 1, row 3 (for the alternative approach). Table B13 includes an additional row to account for the consumer surplus associated with baseline connected households.

30 years (for the alternative approach; 1B), (2) alleviating credit constraints for grid connections, (3) eliminating transformer breakdowns, (4) eliminating the connection delays, and (5) eliminating all project construction cost leakage.[54] We examine these individually and then assess the effect on social surplus of combining them all in what we call the "ideal scenario," which can be thought of as perhaps the best-case scenario for a low-income country considering mass rural residential electrification.

The first row of table 5 presents the base results from the above analysis, including the average connection cost (at 100% coverage) of $739 and average consumer surplus from the experimental approach of $147 and from the alternative approach of $293. As Kenya continues to develop, it is likely that incomes and energy consumption will grow. To predict the effect of income growth on consumer surplus, we focus on the relative differences between households with low- and high-quality walls. Specifically, we first estimate that households with low-quality walls would need to have

[54] In table B13, we include an additional adjustment that accounts for the consumer surplus associated with households that were already connected at baseline. This adjustment does not greatly alter our conclusions.

income growth of 3% annually over 10 years in order to reach the income of households with high-quality walls.[55] We then calculate the difference in experimental demand curves between these groups (fig. 2*B*) to be equivalent to a 2.2% annual growth rate in consumer surplus over 10 years. Extrapolating these relationships over a 30-year period, consumer surplus per household reaches $285, thus increasing the main estimate of consumer surplus by $139 (improvement 1A).

We further refine the estimates of consumer surplus in the experimental approach by relaxing credit constraints, using the valuations from the stated-WTP question without time constraints described above (improvement 2).[56] This more than triples consumer surplus, but it is not enough to alter the conclusion that social surplus is likely to be negative. Similarly, while rapid electricity consumption growth in the coming 30 years (at 10% per year) leads to a large increase in consumer surplus in the alternative approach, it is not enough to offset the up-front average connection cost.

We next turn to simulated improvements in service provision that address transformer breakdowns (improvement 3) and grid connection delays (improvement 4), both of which somewhat increase consumer surplus, in the first case by increasing the number of days of service and in the second case by assuming that consumers get access to power sooner. As a rough approximation, we assume that demand estimates scale linearly. Neither improvement on its own is sufficiently large to overturn the negative–social surplus conclusion.

Finally, we simulate a reduction in total construction costs of 21.3%, consistent with the degree of overinvoicing of construction poles documented in the data (improvement 5). This leads to a sharp reduction in total costs, under the assumption that this leakage is simply "waste"; leakage would be less socially costly if viewed simply as a transfer from taxpayers to contractors (though it would still result in some deadweight loss associated with the cost of raising funds).

The bottom row presents the ideal scenario, in which all improvements are simultaneously implemented. The use of the preferred experimental estimates incorporating the easing of credit constraints and future income growth results in a social surplus gain of $83. The alternative estimates using electricity consumption (and assuming rapid future consumption growth)

[55] As a proxy for income, we use end-line food consumption per capita. Note that we did not have a comprehensive baseline measure of household income or consumption. Our baseline monthly-earnings measure—calculated as the sum of respondent profits from businesses and self-employment, salary and benefits from employment, and household agricultural sales—is imperfect, as it excludes earnings from other household members as well as subsistence farming.

[56] Note that the alternative approach reflects consumer surplus from a grid connection largely absent credit constraints, since it presumes that the household already has a connection.

are more positive, with a social surplus gain of $166. The bottom line is that there are optimistic assumptions regarding the reduction of corruption and improvements in electricity service quality, together with sustained economic growth, under which mass rural residential electrification appears to increase social surplus.

There may also be additional benefits that are not captured by household WTP that could make this calculation appear more positive. First, as outlined in section II.B, there may be spillovers from private grid connections, including any benefits that local unconnected households experience. Yet, as mentioned in section V.A, we find no evidence of an interaction between the treatment indicators and the local baseline electrification rate.[57] Additionally, as noted in section V.D, we find no compelling evidence of spillover impacts in R1 data for local unconnected households along a range of economic and noneconomic outcomes, although these effects are relatively imprecisely estimated.

Second, grid connections are long-lived, but their long-term benefits may not be fully reflected in WTP if households have limited information about the future income or broader social benefits of electrification or as a result of imperfect within-household altruism: for instance, if children stand to gain the most from indoor lighting in the evening (if it boosts learnings and future earnings) but their parents do not fully understand these gains or incorporate them into decision-making. However, as noted above, we do not find evidence for child test score gains in connected households in the medium run.

Further, other factors may push up costs, making rural electrification less attractive. The per-household connection cost would be substantially higher under a policy in which only a subset of households were connected to the grid (given the fixed costs of expanding the local LV network) than under the mass-connection case that we assume in table 5. Most importantly, access to modern energy could generate negative environmental externalities from higher CO_2 emissions and other forms of pollution.

Finally, we have considered neither the costs nor the benefits of the initial investment to extend the high-voltage lines and install transformers in each sample community. Each installation required a relatively large investment—the median cost per transformer is $21,820 (Lee et al. 2016)—and the social surplus gains from powering the targeted public facilities, while potentially large, have not been measured. Our analysis treats these costs as sunk and focuses solely on the economics of electrifying "under-grid" households, conditional on existing infrastructure. This is

[57] Note that we cannot rule out the possibility that any negative effect of these spillovers on take-up due to free-riding is offset by a competing positive "keeping-up-with-the neighbors" mechanism (Bernard and Torero 2015), or that greater learning about the private benefits of electricity and/or correlated household characteristics are present.

the policy-relevant question in our setting, given the expanding Kenya LMCP, but the cost of transformer installations would need to be considered in many other African and Asian settings.

VII. Conclusion

Over the past century, rural electrification has served as a key benchmark for economic development and social progress. The United States began its rural mass electrification program in the late 1930s, although it required 2 decades to reach 90% of households (Kitchens and Fishback 2015), China did so in the 1950s, and South Africa launched its initiative in the 1990s. Today, access to energy has emerged as a major political issue in many low-income countries.

However, the extent to which increases in energy access should be driven by investments in large-scale infrastructure, such as grid connections, or small-scale decentralized solutions, such as solar lanterns and solar home systems, remains contested. Does Africa's energy future even lie with the grid? Although our findings suggest that rural household electrification may reduce social surplus, they do not necessarily imply that distributed solar systems are any more attractive than the grid or that the patterns we identify are universal across time and space. In fact, the evidence—on the pervasiveness of bureaucratic red tape, low grid reliability, and household credit constraints, all of which would suppress demand, and inflated construction costs from leakage—suggests that the social surplus consequences of rural electrification are closely tied to organizational performance as well as to institutions. We show that settings with better performance by the electricity utility—with fewer losses due to leakage and service that is more responsive to customers—may see shifts in both the cost curve and the demand side, and in such settings mass rural electrification may potentially be socially desirable.

Another possibility is that mass electrification is indeed transformative and reshapes social, political, and economic interactions, perhaps in the long run, but that individual rural households do not internalize these benefits, and they are neither reflected in private demand estimates nor observable in the medium-run follow-up data collected 16 and 32 months after connection. Rural Kenyan households today may, on average, be too poor to consume meaningful amounts of electricity, but perhaps after another decade (or two) of sustained income growth they will be able to purchase the complementary appliances needed to fully exploit electrification's promise.

Decisions to invest in large-scale energy infrastructure programs are associated with major opportunity costs and long-run consequences for future economic development and climate change, especially in sub-Saharan Africa, where access to electricity lags that in the rest of the world. The findings of this study indicate that connecting rural households today may not necessarily be an economically productive and high-return activity in the world's poorest countries. The social returns to investments in transportation, education, health, water, sanitation, and other sectors—indeed possibly including the electrification of industrial sites or urban areas—must be compared to investments in rural electricity grid expansion to determine the appropriate sequencing of major public investments. Given the high stakes around these decisions and the limited evidence base, there is a need for research in several areas, including on the impacts of increasing the supply of electricity (in terms of both access and reliability) to different types of consumers, such as commercial and industrial consumers; identifying the patterns and drivers of consumption demand, including for energy-efficient appliances; and determining routes to improving electric utility organizational performance.

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