Bandwagon Effects in Poor Communities
Experimental Evidence from a Rural Electrification Program in Ethiopia

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This paper relies on an original dataset on a new rural electrification program in Ethiopia. It assesses the importance of bandwagon effects in determining individual connection choice. Combining global position system information with the random allocation of discount vouchers for connection, we show that both price and neighbors' connection behavior have large effects on a household's connection decision. The effect is also shown to decrease by distance; that is, no peer effect is found for neighbors 100 meters away or farther. Absent short term effects of electrification on time allocation, productive activity and knowledge of the advantage of electricity, our results further suggest that the observed bandwagon effects are likely related to 'keeping up with neighbors' type of mechanism. With many development interventions constrained by low take-up rates and consecutive limited sustainability, these results carry important implications for the design of development interventions.

1. Introduction

Economists have long recognized the importance of social comparisons in determining individuals' consumption choices; in other words, the demand for a commodity is increased when others are also consuming the same commodity. In the late 1940s in particular, researchers emphasized the lack of correspondence between lateral summation of predicted individual demands with general demand levels (Morgenstern 1948), the existence of demonstration effects (Morgenstern 1948) or bandwagon effects (Leibenstein 1950) in consumption choices, and the consequential importance of relative income in determining consumer behavior (Duesenberry 1949; Modigliani 1949). Although the debate was revived in the late 1970s, it is significant that these initial studies occurred in the United States after World War II, when "systems of ascribed social status and social stratification were breaking down or had effectively disappeared" (Mason 2000).

Social comparisons are also relevant in developing countries today, as traditional norms of consumption and technology-adoption behavior are gradually eroded under the influence of population pressure, market penetration, and access to global media (Platteau 2006). It is striking, for instance, that mobile phone penetration in countries such as Kenya, Niger, or Haiti has far exceeded expectations (Aker and Mbiti 2010), despite important significant costs and sometimes limited productive use (Kebede 2010). Although not having a cell phone when everyone else does can constitute a handicap, several studies suggest that considerations of social status are also important determinants of adoption, at least in the early phases.[1] Social comparisons may also explain part of the apparent paradox described in Banerjee and Duflo (2007), whereby otherwise food-limited households in various countries spend a significant

[1] It is worth noting that marketing companies are well aware of such effects and routinely design promotional campaigns to trigger these effects.

amount of (needed) resources on such items as festivals and other visible consumption items. Some further evidence of these phenomena can also be found in the rather voluminous literature on relative consumption and subjective well-being, where keeping up with one's neighbor is a strong determinant of consumption choices (see Fafchamps and Shilpi [2008] or Frey and Stutzer [2002] for a review).

A better understanding of diffusion effects and of the role that such social comparison-based mechanisms can play bears significant consequences for the design of development policies. In fact, depending on their size, such social multiplier effects can explain why particular commodities, technologies, or services converge toward high or low adoption equilibrium. Such an understanding would be helpful if one wanted to promote consumption of the type of goods that have limited private returns but that exert positive externalities on others' well-being. One could, for instance, explain the rather low adoption rate of improved stoves, despite years of promotional campaigns, by the lack of promotional policies that have been able to trigger social comparisons (Burwen and Levine 2011). Such an understanding would also be useful if one aimed to limit consumption of limited productivity items that come at the expense of more productive items—think, for example, of a trade-off between designer clothes and investments in education. Finally, numerous development programs fail to reach the participation levels necessary to ensure their sustainable provision in the medium or long run. Thus, understanding the role that social comparison plays in the adoption of new commodities, technologies, or services could help in the design, implementation, and sustainability of development policies.

A number of studies (for example, Becker 1974; Granovetter and Soong 1986; Bernheim 1994; Mui 1995; Akerlof 1997; Sobel 2005) provide further theoretical ground for these effects through such traits as envy, the need for conformity or social status, and other social dynamics that affect consumption. On the empirical side, however, researchers have faced challenges in attributing the observed differences in consumption patterns across groups that have otherwise similar underlying fundamentals, to such social-comparison based bandwagon effects (Scheinkman 2008).

First, one must separate what can be attributed to social interactions from other factors that can also produce homogenous behavior across neighbors. Following Manski (1993), homogenous behavior within groups may be driven by sorting effects, whereby similar individuals belong to the same groups; by contextual effects, whereby individuals within groups are confronted to the same environmental factors; or by actual social interactions. Within the latter, Manski further distinguished between exogenous interactions, in which individuals are affected by their neighbors' characteristics, and endogenous interactions, in which individuals influence one another through their actual behavior. Only the latter leads to the so-called social multiplier in which we are interested (Scheinkman 2008).

Second, one needs to interpret the said endogenous interactions. Manski (2000) proposed three alternative types of endogenous social interactions. *Constraints interactions* relate to the fact that one's behavior may affect (positively or negatively) others' constraints in adopting such behavior—for instance, if one's demand for a good increases the price of this good for others. *Expectation interactions* rely on the fact that by observing others' behavior and the corresponding results, one obtains more information regarding the potential benefits of these actions. Such interactions are more often framed as social learning. Finally, *preferences interactions* characterize those situations in which individuals' preferences for a particular set of actions depend on the actions chosen by others. Although constraints and expectations interactions make more sense to economists, it is noticeable that preference interactions are more prevalent in other social sciences. To our knowledge, only Banerjee et al. (2011) attempted to separate these effects in the context of a developing country. Investigating participation rates in a microfinance program in southern India, they found no peer effect over and above that of information transmission, suggesting that expectations interactions dominate in this case.

This paper explores these issues in the context of a new rural electrification in Ethiopia. The setting is arguably ideal, as no electricity was available in the surveyed communities when we collected baseline data. Shortly after the baseline survey, electrical lines were installed in the community. Connection to the grid is expensive, however, ranging from $50 to $100 (depending on one's distance to the nearest electrical pole), and only a proportion of the sampled households chose to connect to the grid over the following 12 months. This study relies on the random allocation of non-transferable discount-towards-connection voucher, household global position system (GPS) locations and households' connection dates, to identify the presence of endogenous interactions (see Kremer and Miguel (2007), Dupas (2010) and Devoto et al. (2011) for similar approaches). Our results show that neighbors' connection behavior have large effects on a household's connection decision. The effect is also shown to decrease by distance; that is, no peer effect is found for neighbors 100 meters away or farther.

While our data does not allow us to directly attribute the observed bandwagon effects to preference interactions, several indirect evidence suggest that constraint interactions and expectations interaction cannot together account for the entire effects observed. In particular, for those that did choose to connect, we observe only marginal productive use of the new energy source and find that lighting is by far the most important use of electrification. However, no (short term) effects are found on time households' time allocation, and in particular on those that were expected to change as a result of electrification such as children study time, or time spent collecting woodfuels. There is also no evidence of a reduction in energy bill, given the number of available and more affordable (though lower-quality) substitutes for electrical lights. Finally, we find that the identified bandwagon effects are much stronger for those households with highest pre-program perception of the benefits of electrification. Thus, with limited observable benefits and high ex-ante knowledge of electricity, these results suggest that expectations interactions are not the main driver of the observed bandwagon effects.

Further, the field setting allows for only limited constraint interactions. First connection price is fixed by the Electrical utility and cannot be reduced by the number or neighbors simultaneously connecting to the grid (as would be the case in so called spider-web electrification). Second, the main electrical implements used are light-bulbs which are readily available and which price is unlikely to be lowered by increased local demand. Finally, one could argue that enhanced lighting in electrified households generates negative externalities on non-connected ones, for instance through more frequent visits to the former at the expense of the latter. Yet, no such effect is found in households' time allocation to entertain visitors. Thus, the observed bandwagon effects seem weakly related to such constraint interactions.

With limited expectation and constraint interactions (at least in the short time-span of the study), preference interactions offers a reasonable explanation to the bandwagon effects observed. In fact, households' electrification status is readily observable by all neighbors through the drop-down wire that connects a house to the nearest electrical pole, directly enabling social comparisons. And while our data does not allow us to directly test for such effects, a number of case-studies in various other contexts suggest that electrification often carries a social status dimension in rural communities. At the same time, anthropological literature often suggests that one is often willing to invest significant resources, in order to keep-up with her neighbors' social recognition.

The paper proceeds as follows. Section 2 positions the study within the broader debates on rural electrification in Sub-Saharan Africa. Although investments in the sector were high until the 1980s, low connection rates have contributed to their abandon. Today, despite renewed investments, rural electrification programs continue to struggle with low household connection rates, jeopardizing their sustainability. Section 2 further describes the Ethiopian context in which ambitious rural electrification initiatives are being taken, although household-level barriers to connection are still weakly understood. Section 3 provides additional information on the study design, along with a number of descriptive statistics on household-level determinants of electrical connections and use of electricity, as well as on the impact of electricity on households' time allocation.

For illustrative purpose, Section 4 proposes a simple model of the consumption behavior of two goods, one of which provides status-related utility in addition to the intrinsic value of its consumption. Drawing from Granovetter (1978) and Akerlof (1997), we show how such a model behaves through time and space, leading to various levels of equilibrium consumption in subcommunity clusters of households. Two separate propositions are thus extracted. First, social comparisons-based bandwagon effects are triggered by richer individuals, for whom intrinsic value is a sufficient condition to connect to the electrical grid. These effects thus only apply to those poorer households that would not have connected without others' decisions to connect. Second, such effects are affected by one's ability to observe others' consumption behavior, which diminishes with distance between households. This effect, in turn, may lead to the existence of subcommunity clusters of high or low connection rates, as discussed in Akerlof (1997).

Our empirical strategy is presented in Section 5. Specifically, we rely on three separate sets of information. First, we collected the GPS coordinates for each surveyed household. With a rather large per-community sample, these coordinates enable us to estimate the number of connected households living within x meters of one's habitation. Second, we use the nontransferable discount-toward-connection vouchers randomly allocated to a subset of community members before electricity was provided to the community.[3] Connection price being an important driver of a household's choice to connect, these vouchers provide an exogenous variation in the number of connected neighbors within a particular distance radius. Lastly, for those households that did connect between baseline and follow-up survey, we collected the exact date of connection. This further enables us to measure through time the number of connected neighbors with or without a voucher living within x meters of a house. Together, these three sets of data enable us to reliably

[3] See Bernard and Torero (2011) for further details on the study design.

estimate the extent to which an individual's choice to connect is influenced by others' choices and to assess how such influence varies by distance from an individual's location.

Our results are consistent across various sets of estimations and point toward the existence of important endogenous interaction in connection behavior (Section 6). Further, we find that such effects decrease with distance between a household and her neighbors, explaining the presence of clusterlike connection behaviors within communities.

Finally, we test for competing explanations to the *bandwagon* effect observed. First, we split our sample between those individuals with very high knowledge of the advantages and disadvantages of electricity at baseline and those with lower knowledge. We find high bandwagon effects for those households with high knowledge, but no such effects for those with lower initial knowledge of the advantages and disadvantages of electrification, suggesting limited social learning effects. Second, we verify whether the distribution of vouchers in itself could have triggered such effects. For this, we compute price elasticities of connection, using contingent valuation questions administered at endline on non-connected households. We find that the obtained elasticities are very similar in magnitude to that of a voucher effect. Section 7 concludes and discusses further research questions and potential policy implications.

2. Perspectives on Rural Electrification and Connection Behaviors

Rural Electrification and Connection Rates in Sub-Saharan Africa

With fewer than 10 percent of rural households having access to electricity in 2000, Sub-Saharan Africa lags far behind rural electrification rates in all other regions (Haanyika 2006). Recent years have seen major increases in rural electrification programs in response to this gap, under the assumption that better access to a clean and reliable energy source will significantly promote rural growth, mitigate urban migration, enhance educational performance and health outcomes, and reduce environmental pressures through reduced wood consumption. Although it is not an explicit target of the Millennium Development Goals, many believe that electricity is a necessary condition to attainment of the goals in rural areas (Modi et al. 2005). Thus, the World Bank (2009) recommends that 25 percent of investments in the energy sector (about USD 10 billion per year) be allocated to the production and distribution of electricity in rural areas.

It is worth noting, however, that such interest in rural electrification programs is not new and was very much present until the beginning of the structural adjustment periods in the early 1980s (see Bernard [2010] for a review). At that time, rural electrification programs represented 10–20 percent of Africa's energy budget, itself comprising 25 percent of African governments' public investment budgets (de Gromard 1992). Yet the cost–benefit ratios for such investments were soon deemed too low, and rural electrification programs were mostly abandoned until their recent renewal. Two important factors contributed to the weak assessment of rural electrification benefits. First, connection rates in electrified communities remained relatively low, with only 25–50 percent of targeted households effectively connecting to the newly installed grids. Second, productive use of electricity remained marginal, and loads were thus insufficient to justify the necessary heavy investments in power lines.

Weak connection rates remain an important challenge today. For instance, studies in various countries have found that the proportion of connected households in grid-electrified villages is 12 percent in Botswana (Ketlogetswe, Mothudi, and Mothibi 2007), 30 percent in Senegal (ESMAP 2007), and 5 percent in a solar electrification scheme in Kenya (Jacobson 2007). These low rates contrast with an apparent important demand for rural electrification. For instance, according to a recent UNICEF study, rural households in Nigeria ranked electricity as their second priority, after safe water but before health centers, roads, education, and fertilizers (ESMAP 2005).

Several explanations have been proposed to explain rural households' low connection rates, with price barriers being the most important. Despite important subvention, connection fees usually range between \$50 and \$250, which may be prohibitive for poor households. As evidence, Heltberg (2003) showed that in Ghana and South Africa, fewer than 5 percent of rural households in the lowest revenue quintile connected to electricity, whereas this rate reached between 25–50 percent for the highest quintile. These findings have recently led to a reconsideration of traditional electrical consumption-based subsidies, which mostly benefited richer households, in favor of so-called smart subsidies for connection targeted at the most needy households (see Barnes and Halpern [2000] for a discussion).

A second constraining factor may relate to poor households' weakly understood billing systems and the fear of flat-rate commitment in the face of these households' difficulty in forecasting revenue streams. For instance, Peters, Harsdorff, and Ziegler (2009) found that among those households that did connect, most tended to consume much less power than their flat rate would enable them to. Solutions such as prepaid electrical meters, akin to those available in the cell phone industry, are now being promoted as a means to overcome such constraints.

Lastly, evidence points toward the importance of others' connection decisions to the individual's decision to connect. One may, for instance, need to observe a neighbor's use of electricity in order to assess the potential benefit of one's own eventual connection (Ranganathan 1993). Or, as tested in the present paper, one's decision may in part be linked to a need to conform to others' connection behavior. This finding has been observed in rural Kenya, where Abdullah and Jeanty (2011) found evidence of a sort of class distinction between those who have and those who do not have electricity; in Ghana, where Abavana (2000) reported an elevated social status of those who did connect; or in Zambia, where Gustavsson (2002) found that clients of a solar program reported feeling that their life had become more urbanlike.

Such types of social interaction–based factors, in turn, may result in large differences in connection rates across otherwise similar groups of households. For instance, in their study of 27 villages in Botswana, Ketlogetswe, Mothudi, and Mothibi (2007) found important differences in connection rates across nearby and similar villages, ranging from 2 percent in some villages to 27 percent in others. This finding, in turn, suggests that policies targeting social interaction–based mechanisms may help trigger the type of social dynamics necessary to reach a higher level of connection rate equilibrium.

Barriers to Connection in Ethiopia

With a GDP per capita of around $110, Ethiopia is by all accounts one of the poorest countries in the world. Despite significant GDP growth in recent years, access to basic services remains very limited for its 85 percent rural population. For instance, as of 2000, only 11 percent of rural households had access to an improved water source, 4 percent had access to improved sanitation, and less than 1 percent had access to electricity within their home (Estache and Fay 2007).

Over recent years, improved access to electricity in rural areas has become an essential component of the federal government of Ethiopia's Agricultural-Led Development Strategy (ADLI). Accordingly, rural electrification is seen as an important input to increase agricultural productivity (through irrigation), as well as to enhance agroprocessing via the development of small-scale rural industries. This input is further justified by the fact that as of today, 77 percent of all energy use in the country is extracted from biomass—essentially fuelwood—most of which is consumed in rural areas. With increased population pressures, an increased need for agricultural land, and a lack of major tree-planting programs, important concerns are thus raised with regard to the sustainability of this ongoing energy trend (Bayissa 2008).

To this end, in 2000, the federal government of Ethiopia launched its first five-year Power Sector Development Program (PSDP), followed by a second one in 2005. On the supply side, these plans are essentially targeted at the country's immense, untapped hydropower potential, estimated at nearly 30,000 megawatts (Wolde-Ghiorgis 2002). To ensure a gradual shift from traditional energy sources to modern sources, the plans also include major efforts on the distribution side, particularly in rural areas. As such, the Universal Energy Access Program (UEAP) aims to supply electricity to 1,000 major villages within the coming years. Within each selected village, households will then be responsible for paying the costs of connecting their house to the main line, which includes the cost of a drop-down line from the nearest pole and the cost of installing a meter. Overall, connection prices may range from 500 to 1,000 Ethiopian birr (ETB),[4] depending on a house's distance to the nearest pole. In a country where 80 percent of all people live on fewer than two dollars a day (UNDP 2006), these costs are often unaffordable for a large number of households; thus, connection rates are expected to be low.

Study Design

As part of a broader effort to measure and understand barriers to connection, the present study sought to assess households' responsiveness to price incentives in order to design targeted connection subsidies—so-called smart subsidies. Specifically, the study relies on an experiment in which discount vouchers of 10 percent and 20 percent were randomly allocated to households in selected village communities that were soon to be electrified under the UEAP program. In each village, the allocation of vouchers was done at random during a clear and transparent public lottery based on administrative village listings.[5] We further used a rather complex voucher design involving watermarks, official stamps, and unique serial numbers to reduce the risk of falsification. In addition, clear instructions regarding the nontransferability of the vouchers were

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[4] Roughly equivalent at the time of our baseline survey to US$50–100.

[5] See Bernard and Torero (2011) for further description of the experiment.

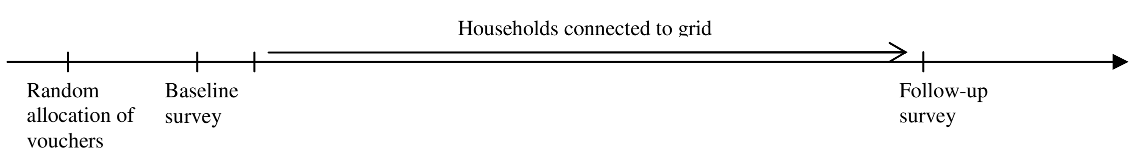
given both in writing and orally, and each recipient's name, national identification number, and address were written on the voucher at the time of distribution. As shown in Table 2.1, Panel 1, the random selection of households to receive a voucher was fairly well executed, such that no differences in the characteristics of recipients and nonrecipients are found at baseline. The study's sequence is described in Figure 2.1, in which the baseline and endline surveys are 12 months apart.

Table 2.1—Descriptive statistics and randomization test of voucher distribution

	Mean	Standard Deviation	Voucher = 0	Voucher = 1	Difference: p-value
Panel 1. Households' Baseline Characteristics					
Consumption expenditures (*1,000 ETB)	6.34	4.03	6.11	6.44	0.32
Age of household head	41.6	14.92	40.76	42.17	0.26
Gender of household head (1 = male)	0.82	.	0.82	0.81	0.84
Household size	5.26	2.47	5.14	5.33	0.39
% income from self-employed agriculture	53.51	38.40	44.86	42.65	0.49
% income from self-employed nonagriculture	31.23	36.69	31.15	31.33	0.95
% income from trade activities	5.78	17.39	5.19	6.14	0.51
% income from salaried activity	14.69	31.46	12.59	15.94	0.20
Distance to nearest pole (*10 meters)	92.63	107.89	12.59	15.94	0.20
Panel 2. Households' Neighboring Density					
# neighbors within 10 meters	0.34	0.77	0.35	0.34	0.88
# neighbors within 20 meters	0.96	1.65	0.90	0.98	0.54
# neighbors within 30 meters	1.82	2.87	1.77	1.84	0.78
# neighbors within 40 meters	2.84	4.56	2.77	2.88	0.78
# neighbors within 50 meters	4.03	6.51	3.85	4.12	0.61
# neighbors within 60 meters	5.15	8.05	4.96	5.24	0.67
# neighbors within 70 meters	6.33	9.28	6.09	6.45	0.63
# neighbors within 80 meters	7.46	10.21	7.35	7.53	0.83
# neighbors within 90 meters	8.62	11.05	8.59	8.68	0.92
# neighbors within 100 meters	9.72	11.64	9.93	9.74	0.84

Note: ETB = Ethiopian birr.

Figure 2.1—Study sequence



Our sample is drawn from eight village communities in southern Ethiopia. In each site, 90 households were randomly selected for a survey at the time of the lottery, some of which were further selected to receive a voucher. Out of these, however, we later found that a number lived too far from the grid to be considered for electrification, so no actual household choice could be observed. Overall, our sample varies from 68–89 households per village, which corresponds to roughly 10 percent of the average village population. Within these households, an average 65 percent were provided with a discount voucher.

For each surveyed household, baseline and endline questionnaires included the standard set of demographic and income-consumption expenditure modules, along with specific modules dedicated to energy usage and geographic position system (GPS) location of the compound's entrance. For those households that had connected in the 12 months before the follow-up survey, the exact date of their demand for connection was recorded from official Ethiopian Electric Power Corporation (EEPCo) documents in their possession.[6] Finally, we used GPS coordinates of each household to further assess the distance to the nearest electrical pole and hence proxy connection prices. Connection costs may vary by up to 35 percent, depending on the length of the drop-down wire that connects a house to the nearest pole. As reported in Table 2.1, we find no significant differences in mean distance to pole between voucher recipients and nonrecipients (Panel 1). Further, the spatial distribution of vouchers was not geographically clustered—a point of importance for the following analyses—as shown by their independence from the density of housing around an individual's house (Panel 2).

3. Descriptive Evidence

This section further sets the study's stage through descriptive statistics on households' connection behavior, use of electricity and impact on time allocation. At baseline, households were asked to report their degree of agreement with a number of statements displaying potential advantages and disadvantages of electricity, wood, and kerosene to perform everyday activities. As reported in Column 1 of Table 3.1, the overwhelming majority of respondents strongly agreed with most of the statements provided in Panel 1, while a much weaker proportion agreed with statements provided in Panel 2. In comparison, respondents reported little agreement with positive statements regarding kerosene and fuelwood, but widely agreed with the disadvantages presented for these fuels. Kerosene is perceived as expensive and not appropriate for lighting or cooking. Furthermore, fumes from kerosene are considered toxic. Results for fuelwood showed that although it may provide better taste when cooking food, wood is scarce, contributes to deforestation, and is relatively expensive when purchased from the market. The majority of respondents also mentioned the important health hazard caused by smoke from wood combustion within the house.

[6] In each selected village, EEPCo (Ethiopia's national power utility) proceeds along the following steps. First, the main line is installed in the village, usually following the main roads. Once the line is installed and ready to operate, the utility sets up an office in the community that will stay in place for at least a few years. EEPCo then announces that registration is open so that each interested household head can indicate, by paying ETB10, that the household is interested in connecting its house. The cost of connection, however, depends in part on the length of the drop-down wire from the nearest pole and the suitability of the house to be electrified. For those households that have registered, EEPCo inspectors estimate the total connection costs that the households will have to pay. Provided the household can cover these costs, a contract is signed, and electricity is installed. It usually takes 5–10 days from the date a household formalizes a demand for connection and the time the house is effectively connected. Because the office is permanent, households can decide to connect any time after the EEPCo office is set up. It is also worth mentioning that as long as the EEPCo office exists in the village, no informal connection between households themselves—the so-called spiderwebs often observed in African cities—can occur.

Table 3.1—Households' perceptions of electricity benefits

	(1) % strongly agree*	(2) % citation as in main three benefits**
Panel 1. Advantages		
Electricity provides better illumination than kerosene oil.	97.0	69.8
Reading is easier with electric lamps than with kerosene lamps.	97.3	22.4
With electricity, children would study more at night.	93.0	30.0
In the electric light, one feels secure at night.	90.0	18.9
Electric lamps do not cause health hazard like kerosene lamps do.	92.2	52.7
Running TV by electricity is less expensive than by battery.	86.2	22.0
It is difficult to work at night without electricity.	82.2	20.8
It is easier to entertain guests in the evening if there is electricity.	95.3	16.9
Electricity is important for our local water supply.	81.0	14.9
Cooking with electricity does not cause smoke.	89.2	13.2
Life would be much easier with electricity.	87.3	8.2
Panel 2. Disadvantages		
Children would waste their reading time by watching TV.	26.1	61.1
Electricity often causes accidents that may lead one to death.	54.4	84.7
Cooking with electricity is not very convenient.	9.5	39.6
Electricity is very expensive .	17.1	45.8
Accessories (bulbs/meters) are very expensive in electricity.	18.8	37.1
Electricity supply is often irregular and low voltage.	9.0	23.2

Notes:
* Response choices varied between "strongly agrees," "tends to agree," "tends to disagree," '"strongly disagrees," and "does not know." The percentage of "does not know" answers averages 2.8 percent of the answers and never exceeds 10 percent.
** Within each panel, respondents were asked to identify the three most important advantages that they perceived from electricity from among the proposed statements. That is: respondents were first asked to cite the three main advantages, and later the three main disadvantages. Column 2 reports the percentage of households who reported the item as one of the three main advantages (disadvantages) of electricity.

In sum, we find that households are rather well informed about the potential advantages and disadvantages of electrification, in contrast with Ranganathan (1993), for whom low connection rates are partly related to households' limited knowledge of the potential uses of electricity. In addition, our results show that electricity is by far most households' favorite energy source, and 99 percent of respondents indicated that electricity carries more advantages than disadvantages. Overall, Table 3.1 suggests a high degree of knowledge about electricity, most likely due to the majority of households having been exposed to electricity in nearby cities or markets. It is also worth noting that, among non-connected households at endline, the vast majority pointed towards connection costs as the main constraint to their connection decision.

Column 2 provides further indications about households' intrinsic valuation of electricity. As reported in Panel 1, electricity is essentially seen as a substitute for kerosene when used for illumination. Accordingly, electricity provides better lighting and lower health hazards than the former, though Panel 2 also highlights households' fear of potential electrical accidents. In comparison, cooking or powering a television rank far lower in terms of benefits from electrification.

We now turn to the effective use of electrical power by those households that decided to connect over the course of the study. Specifically, we ask whether households use electricity for productive purposes or mainly for their own comfort. The first piece of evidence can be drawn from the actual electrical installation, as reported in Table 3.2. Accordingly, 87 percent of connected households' installation does not allow for more than four light bulbs; in 95 percent of the cases, it allows for fewer than three sockets. In our sample, only one household had an electrical installation capable of powering a refrigerator, a motor, or a water heater. In such conditions, the productive uses of electricity are restricted to those derived from better lighting within the house.

Table 3.2— Electric installation capacities

	% connected households with … lighting points	% connected households with … socket outlets	% connected households with … motor/fridge/heater/stove socket
0	0.00	49.11	99.64
1	19.93	36.30	0.36
2	29.54	12.10	0.00
3	22.42	2.14	0.00
4	15.30	0.36	0.00
> 4	12.81	0.00	0.00

We further investigate households' use of lighting derived from electrical connections. Specifically, we ask what proportion of time lit by electricity is used for several types of activities. The three most important are reported in Table 3.3. Accordingly, the majority of electrical light is used for non-(directly)-productive activities, such as reading, studying, cooking, and others. Use of electric light for productive purposes is only marginal. Overall, the results thus far suggest a high demand for electricity by households in our sample, though not directly related to productive use.

Table 3.3— Use of electrical light

	Categories	1st usage	2nd usage	3rd usage
1	Reading/studying	56.52	57.42	35.72
2	Other domestic uses (light for eating, cooking, entertaining friends, and so on)	38.27	30.69	57.14
3	Home business (handicraft, weaving, sewing, trading, and so on)	5.22	11.88	7.15

Turning to the determinants of households' effective demand for electrical connection, we relate in Table 3.4, households' connection status at the end of the study to a set of characteristics measured at baseline. As expected, we find in Column 1 that income, proxied by levels of consumption and expenditures, is a strong predictor of a household's decision to connect.

Further, male-headed and larger households are more likely to connect, which upholds the fact that women-headed households tend to be poorer and that larger households may benefit from economies of scale to overcome such fixed costs as electrical connection. We also find that those households with a steady income flow, such as those with a salaried activity, are more likely to connect. In Column 2, we introduce price-related variables, which seem to be strong drivers of connection: distance to pole is negatively correlated with connection status, whereas having been allocated a voucher increases one's connection probability by more than 12 percentage points. Finally, Column 3 introduces connection rates among other households within the community; although statistically significant, the magnitude of the correlation is marginal.

Table 3.4—Household-level determinant of connection

	Dependent variable: Household has connected to the grid (linear probability model)			Dependent variable: Connection date (censored at date > 365) Marginal effects at mean of independent variable		
	(1)	(2)	(3)	(4)	(5)	(6)
Consumption expenditures (*1,000 ETB)	0.021 (0.005)**	0.020 (0.005)**	0.017 (0.005)**	–9.558 (3.152)**	–10.067 (3.182)**	–11.146 (3.198)**
Age of household head	0.002 (0.001)	0.002 (0.001)	0.002 (0.001)	–1.392 (0.964)	–1.496 (0.958)	–1.656 (0.943)
Gender of household head (1 = male)	0.119 (0.054)*	0.146 (0.054)**	0.161 (0.054)**	–90.676 (39.508)*	–116.904 (40.349)**	–109.399 (39.748)**
Household size	0.015 (0.009)	0.015 (0.009)	0.019 (0.009)*	–14.365 (5.785)*	–12.096 (5.834)*	–10.813 (5.777)
% income from self-employed agriculture	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	–0.463 (1.033)	–0.012 (1.044)	–0.132 (1.011)
% income from self-employed nonagriculture	0.003 (0.001)**	0.003 (0.001)*	0.003 (0.001)*	–2.245 (1.021)*	–1.641 (1.035)	–1.623 (1.000)
% income from trade activities	0.004 (0.001)**	0.003 (0.001)*	0.003 (0.001)*	–2.699 (1.167)*	–1.955 (1.161)	–1.953 (1.129)
% income from salaried activity	0.003 (0.001)**	0.003 (0.001)*	0.003 (0.001)*	–2.795 (1.032)**	–2.157 (1.044)*	–2.103 (1.012)*
Distance to nearest pole (*10 meters)		–0.006 (0.002)**	–0.006 (0.002)**		3.682 (1.361)**	3.561 (1.335)**
Voucher (1 = yes)		0.123 (0.041)**	0.123 (0.041)**		–72.159 (28.229)*	–72.430 (27.874)**
# connected households in community			0.000 (0.000)**			0.022 (0.010)*
Constant	–0.208 (0.113)	–0.199 (0.121)	–0.255 (0.128)*	817.999 (106.162)**	786.940 (108.868)**	760.273 (107.399)**
Observations	596	563	563	608	563	563

Notes: Robust standard errors are in parentheses. * significant at 5 percent; ** significant at 1 percent.

Results are also consistent in Columns 4, 5, and 6, where we use a Tobit estimator to investigate determinants of households' connection date. As reported, wealthier households tend to connect earlier, as do those having a steady income stream. In turn, connection price tends to delay an individual's connection decision, as shown by the positive coefficient associated with one's distance to the nearest pole and the negative coefficient associated with voucher status – a point of importance when analyzing bandwagon effects through time in Sections 5 and 6. In Column 6, we introduce the number of connected households in the community. Accordingly, each additional connected household in the village is associated with a 0.02 percentage point earlier connection period for the individual—again, a relatively small magnitude.

To further illustrate the eventual effect of peers on an individual's connection behavior, Figure 3.1 maps households' locations, along with their connection status and their distance to the electrical line installed, in one of the eight villages under study. As exemplified by the dashed circles, the picture reveals a number of clusters of connected (black) and unconnected households (white). Furthermore, these clusters do not a priori bear a clear relationship to households' distance to the electrical line, which, as noted earlier, significantly affects connection prices. Finally, these clusters mostly correspond to households leaving less than 200 meters from one-another.

Figure 3.1—Households' locations and connection status, example from a southern Ethiopian village

Source: google map.

Lastly, Table 3.5 reports estimates of the impact of electricity on households' time allocation. For each surveyed household, we collected diary-based measures of time spent on various activities, for up to four individuals including a male adult, a female adult and two children. Specifically, the questionnaire asked at what time the respondent woke up, what he/she did next, until when, what he/she did after, until when, and so on until he/she went to sleep. According to Juster and Staffor (1991), such diary measures while not perfect, are less prone to over-estimation of time allocation than when relying on questions of the type "how much time do you spend on a typical day doing x". To further ensure comparability, all questionnaires referred to the past Monday. Yet, Mondays may sometimes be not representative of typical days. In particular, Monday could be the day of a particular market in the neighborhood, to which households attend and leave their productive activities or a particular religious day which are numerous in the Orthodox Ethiopian context. For this reason, we asked each individual if the past Monday was a particular market day or a particular religious day for him/her, in order to control for it. The results presented below rely on the whole sample but are comparable to those obtained on the sub-sample of households for whom the past Monday was not a typical day.

Table 3.5—Impact of electrification on Time Allocation

	OLS coefficients (Standard errors) (1)	2SLS coefficients (Standard errors) (2)
Dependent variable : Change between Round 2 and Round 1 in per capita time allocated to… (cf notes)		
Agriculture self-employed	-6.36	7.63
	(9.98)	(89.57)
Non-ag self-employed	20.22	58.50
	(15.87)	(132.08)
Other employment	1.20	-17.42
	(5.68)	(53.15)
Household chores	0.49	-69.28
	(10.76)	(98.76)
Child care	-0.56	-52.82
	(5.79)	(51.09)
Time for self	22.11	16.63
	(16.78)	(143.97)
Homework	1.59	-71.97
	(5.56)	(50.34)
Entertain visitors	0.29	-7.17
	(2.71)	(22.26)
Watch TV/listen to Radio	2.41	-1.17
	(11.26)	(92.85)
Firewood/ dung collection	-2.42	9.30
	(1.78)	(16.47)

Notes:

- Total change was aggregated for up to four respondents per household and divided by the number of respondents.
- Each cell reports the estimated coefficient associated to connection at round 2, in a separate estimation including Consumption/expenditure, Household head's age and gender, household size, sources of income and distance to the nearest pole as additional control variables (coefficients not reported).
- Column (2): connection instrumented by households' voucher status (recipient/non-recipient).
- Clustered (village-level) standard errors in parentheses. Each estimate is based on the whole sample of 566 observations.

* significant at 5 percent; ** significant at 1 percent level.

Each line of the table reports the parameter estimate obtained for the connection variable, drawn from a separate regression of the considered time allocation variable onto a household's connection decision and the same set of control variables used in Table 3.4 (for sake of parsimony, the corresponding coefficients are not reported). Column (1) reports simple OLS estimates, while Column (2) relies on the results of Table 3.4 – Column (2) as a first stage to Two-Stage Least Square estimates, where the random allocation of voucher is used as an excluded instrument for a household's decision to connect. Overall, results from Table 3.5 indicate no apparent effect of electrification on time allocation over the course of the study. And while these estimates rely on an imperfect compliance encouragement design applied to a relative small sample, it is likely able to identify the type of important changes in time allocation that could eventually trigger neighbors' change of perception vis-a-vis the benefits of electrification. Note however that such effects may well be present in the longer run such that the results presented in Table 3.5 should merely be interpreted as a lack of households' immediate adjustment to their new electrified status.

Overall, descriptive evidence suggests a rather high demand for electrical connection, which varies positively with income and negatively with connection prices. Village-level correlations between a household's connection decision and that of the household's peers are not conclusive. Yet evidence suggests potential subvillage influences, based on geographic proximity between households. However, such changes are unlikely to be driven by neighbors' observation of significant change in living conditions of those electrified households. In the next section, we develop a simple model to illustrate how social interactions can affect connection choices and how these may lead to the observed geographic clusters of high or low connection rates exemplified in Figure 3.1.

4. Illustrative Model of Bandwagon Effects on Consumption

Social interaction models seek to explain the widely observed phenomenon of large differences in outcomes across groups of individuals, despite limited differences in underlying fundamentals (for example, Scheinkman 2008). In our context, this translates into observing different levels of connection across households or groups of households with apparently similar needs and means for electrification. As exemplified in Manski (2000), several reasons may explain these differences.

The first is constraints interactions, which are driven by the fact that connection to the electrical grid exerts positive or negative externalities on the constraints that others face to connect. This interaction would be the case, for instance, if higher demand for connection affected price or if complementary goods to connection, such as electrical implements, were more available when a larger number of households decided to connect within the community. In Ethiopia, however, price is fixed nationally by the national electric utility, and implements such as lightbulbs, which are the main use of electricity (see Table 3.2 and 3.3), are readily available to all connected households.

The second potential case is expectation interactions, by which an individual would learn the benefit of electricity from another's connection behavior. In our sample, however, the overwhelming majority of households indicated a very positive perception of the benefits of electricity at the baseline, when no one was yet connected, and 99 percent expressed a clear demand for electrification (see Table 3.1). Further, we find no evidence of changes in time allocation of electrified households, nor of use of electricity for productive use. The third is what Manski (2000) referred to as preference interactions, whereby the search for conformity or social status would contribute to an individual's decision to connect to the electrical grid in order to differentiate from one's peers or at least to keep up with them. Qualitative evidence within survey villages and other studies in Africa (for example, Abdullah and Jeanty 2011) suggest that this sort of effect may well be at play in our context.

Since Leibenstein (1950), several theoretical approaches have been proposed to better account for such bandwagon effects in consumer demand behavior. For instance, Becker (1974) defined *social income* as the sum of a person's own income and the perceived monetary value of the relevant characteristics of others which one can influence by one's consumption behavior. In a related vein, Bernheim (1994) drew on the idea that consumption of a given good may reveal one's type, which in turn can lead to more or less esteem from others. A person therefore chooses the level of consumption that jointly maximizes the intrinsic utility derived from consumption as well as the esteem one may draw from others. Focusing on dynamics, Granovetter and Soong (1986) used a threshold model in which an individual's decision to consume a particular good depends on the number of people who decided to consume that good in previous periods. The extent to which previous consumers affect an individual's choice can, in turn, depend on the importance of social ties among consumers. In a similar, although static, fashion, Akerlof (1997) proposed a gravity model in which an individual's influence over others' consumption is affected by social distance between consumers. Our approach draws from various aspects of these models.

Set-Up

We rely on a simple household utility maximization choice in a given period. Accordingly, the household is endowed with an exogenous wealth y and uses it entirely to derive a maximum level of utility from the consumption of two types of goods, x^1 and x^2. Specifically, let x^1 represent a continuous bundle comprising essential commodities, such as food and clothing ($x^1 \epsilon \mathbb{R}^+$). x^2, in turn, represents a novel type of good, such as access to electrification, of which only unit can be consumed ($x^2 = (0,1)$).[7] Given the limited use of electricity for productive purpose and the apparent absence of effect of electrification on households time allocation observed in Section 3, we do not account for possible joint utility of consumption between the two goods and model them as independent consumption items.

Let us first consider a scenario in which electricity is not available within the household's community; let x^{1*} characterize the household's corresponding optimal consumption level. The household's Marshallian demand function is given by $x^{1*}(p_1, y)$, with $\frac{\partial x^{1*}}{\partial p_1} < 0$ and $\frac{\partial x^{1*}}{\partial y} > 0$, where y is the household's income and p_1 is the vector of unit prices for x^1.

[7] Alternatively, one could model the "amount" of electricity consumed, though general results are not affected. Furthermore, in Ethiopia, consumption costs are marginal as compared with connection prices. Modeling connection choices is thus more appropriate in our context.

Let us now provide the household with the opportunity to connect to the electrical grid, such that the household now has the opportunity to optimize its consumption choices between x^1 and x^2. Recall that x^1 comprises essential commodities, such that its consumption level must at minimum meet with the household's most basic requirements. Assuming little complementarities between the two types of goods, $U(c) = u(x^1) + u(x^2)$, the household's willingness to pay for $x^2(\hat{p}^2)$ satisfies the following expression:

$$U(x^1, x^2) = U(y - \hat{p}^2, 1) = U(x^{1*}, 0),$$

which in turn provides an expression for $\hat{p}^2$, as $\hat{p}^2\,(y, p^1)$ and $\frac{\partial \hat{p}^2}{\partial y} > 0$ and $\frac{\partial \hat{p}^2}{\partial p^1} < 0$. With p^2being the actual (exogenous) price of electrical connection, let $\hat{y}$ measure the minimum level of income for one to decide whether to connect to the grid, which is implicitly defined by $\hat{p}_i^2(\hat{y}, p^1) = p^2$. The household's connection choice can then be expressed through the following switching expression:

$$\begin{array}{l} y \leq \hat{y} \rightarrow\ x^2 = 0 \\ y > \hat{y} \rightarrow\ x^2 = 1 \end{array},$$

in which poorer households are unable to connect, and thus electricity is only provided to richer households.

Now let us assume that electricity consumption carries benefits in terms of social status. In fact, whereas x^1 can be consumed without knowledge by neighbors (think of food, for instance), consumption of x^2—that is, connection to the electrical grid—is observed by all. We assume that social status is only derived from the consumption of *visible* goods, as only these types of goods may trigger social comparisons between households. The household now wishes to optimize its utility with respect to both consumption of each good, c, and the social status the household derives from connection to the electrical grid, s. The household's utility function may be expressed as follows:

$$U(c, s) = U(x_i^1, x_i^2) = u(x_i^1) + u(x_i^2) + \sum_{j \neq i} \delta_{ij} \,.\, (x_i^2 - x_j^2) x_j^2.$$

As above, $u(x_i^1)$ and $u(x_i^2)$ capture the intrinsic utility to household i of consuming good types 1 and 2, respectively. Following Sobel (2005), we express an individual's social status–related gains by the weighted sum of differences in consumption of x^2 between i and other members of the community, $j \neq i$. As we shall discuss later, δ_{ij} is a social comparison parameter capturing the importance of social comparisons, which may vary across particular pairs of individuals. Let us assume for now that δ_{ij} is constant and positive for all i and j in our population. As a result, if $(x_i^2 - x_j^2) < 0$, then i's utility will decrease with both j's consumption level and δ_{ij}. The opposite is true if $(x_i^2 - x_j^2) > 0$. In such cases, however, $x_j^2 = 0$, such that the overall effect is null. Thus, our model is essentially one of social conformity, that is where an individual's choice to connect is in part driven by her need to 'keep-up' with her neighbors' connection choice.

In addition, assume for now that other's connection behavior is exogenous. Following the same route as above, willingness to pay is rewritten as $\hat{p}^{2\prime}\left(y, p^1; \delta_{ij}, X_j^2\right)$, with $X_j^2 = \sum_{j \neq i} x_j^2$. Loss of social status, provoked by lagging behind others, produces a disutility, and $\hat{p}_i^{2\prime} \geq \hat{p}^2$, such that the household has a greater incentive to connect if others do so. Again, noting y', the minimum income after which one chooses to connect, greater social status–related utility derived from consumption x^2 implies that $y' < \hat{y}$. This, in turn, can be used to classify households in a manner akin to that of partial compliance treatment literature:

$$\begin{array}{ll} \text{"Never Takers":} & y \leq y' \\ \text{"Compliers":} & y' < y \leq \hat{y}. \\ \text{"Always Takers":} & y > \hat{y} \end{array}$$

Accordingly, *never takers* are those households that would never connect—that is, those households with insufficient means to connect without losing too much utility from lowering their consumption of x^1. *Always takers* are those that will connect in any scenario, even without social status–derived utility. Finally, *compliers* are those households whose connection choice is in part driven by peer pressures. Letφ^C, φ^{NT}, and φ^{AT}measure the proportion of compliers, never takers, and always takers in the population, respectively.

Dynamics

Following Granovetter (1978) and Granovetter and Soong (1986), let θ_i characterize the minimum number of neighbors' connection at previous periods necessary for one to decide to connect.[8] For instance, an individual may only decide to connect after seeing 50 neighbors doing so, whereas someone else may react after observing that 20 neighbors have connected in previous periods. In essence, θ_i is defined by $X_{j,t-1}^{2*}$, such that $\hat{p}^{2\prime}\left(y, p^1; \delta_{ij}, X_{j,t-1}^{2*}\right) > p^2$. For never-taker households, $\theta_i \to \infty$ and $x_{NT,t}^2 = 0, \forall t$; whereas for those within the always-taker population, $\theta_i = 0$ and $x_{AT,t=1}^2 = 1$. Thus, only households within the complier population will effectively decide to connect in response to others' observed connection behavior in the previous period.

Let the distribution of θ_i follow a density function, $f(\theta)$. To keep up with Granovetter (1978), we designate the number of households that have consumed x^2 at time t as $r(t)$. In turn, the total number of purchasers at time $t+1$ is given by the sum of those whose threshold is less than or equal to r: $r(t+1) = F\big(r(t)\big)$, where $F(.)$ is the cumulative distribution function of $f(.)$. At equilibrium, the number of those connected in a given period is equal to the number of those who connected in the previous period: $r(t)^* = F\big(r(t)\big)$. The level of the obtained equilibrium, in turn, depends on the characteristics of the distribution of thresholds, $f(\theta)$.

Households' classification into compliers, never takers, and always takers thus carries implications for the model's time dynamics. First, assume that no electricity is available at time

[8] Following Manski (1993), we assume that non–social interaction forces act contemporaneously, whereas social interaction forces occur with a lag. The assumption is further supported in our context, where one only observes households' connection choices made at previous periods.

$t = 0$, and it only becomes available at time $t = 1$. At time $t = 1$, the total number of connected households is thus limited to φ^{AT}. For $\varphi^{AT} = 0$, no complier will choose to connect at time $t = 2$, and the so-called bandwagon process will be aborted. More generally, the greater φ^{AT}, the greater the chances that it will trigger these effects, such that $\frac{\partial r(t)^*}{\partial \varphi^{AT}} > 0$.

Second, the bandwagon process will continue only as long as individual thresholds are smoothly distributed for those households within the complier population. In other words, the closer compliers are to one another in terms of the threshold, the greater the number of households will have consumed x^2 at the end of the process. If one assumes homogenous (social) preferences, the only difference across households within the complier population is given by the distribution of income, y. Homogeneity of income within the complier population shall therefore lead to higher aggregate connection rates: $\frac{dr(t)^*}{d\sigma_y^C} < 0$, where σ_y^C is the income variance within the complier population.

Clusters

Up to now, we have considered δ_{ij} as being fixed across all pairs of households. In reality, however, when forming social comparisons, one does not attribute the same weight to all households in the population. This idea is discussed in Brock and Durlauf (2001), who distinguished between global interactions, in which the same weight is given to all population members, and local interactions, in which only individuals within one's geographic or social vicinity are given greater weight (see also Moffitt 2001). For instance, one could care only about certain people in one's community (for example, same gender, same social group), such that δ_{ij} takes value 1 if j is in the same group as i; otherwise, it takes value 0. Within each group, a final consumption level of x^2 will be driven by the respective numbers of always takers and compliers and the form of threshold distribution within the complier population. This may in turn lead to potentially different connection behaviors for otherwise similar households belonging to different groups.

Furthermore, within a particular vicinity, greater weight could be given to individuals who are closer in terms of particular characteristics or behavior, and δ_{ij} would be a continuous variable. For instance, Granovetter (1978) argued that the social influence of a friend or family member may be larger than the influence of a stranger. In a somewhat different vein, Akerlof (1997) used a gravity model to describe how individuals may *trade*—that is, in a social interaction perspective—more with individuals who are close by with respect to their consumption pattern. In such a context, δ_{ij} is no longer fixed; instead, it depends on the distance between the two households: $\delta_{ij} = \delta(d_{ij})$, where d_{ij} measures the physical or social distance between the two individuals, and $\frac{d\delta}{dd_{ij}} < 0$.

In places that are very much scattered, δ_{ij} will be small, social multipliers will be weak, and no such bandwagon effects will be observed. In places where a certain level of proximity exists, however, the spatial distribution of thresholds may lead to the creation of what Akerlof (1997) called *subcultures,* whereby clusters of particular behavior are observed within a given community. The straightforward implication in our context is that for a given level of θ, a household may adopt different connection behaviors based on the distribution of always takers, never takers, and compliers within its vicinity.

5. Empirical Strategy

In this section, we further elaborate on our empirical strategy to test the predicted bandwagon-related connection behaviors derived from the illustrative model in Section 4. Empirical identification of such effects directly relates to the empirical literature on peer effects, which has received increased attention in recent years in the fields of education, crime, and other socially influenced behaviors. The purpose is to try to explain the existence of large differences in outcomes across groups that are composed of otherwise similar individuals. This idea, in turn, relates to the fact that individual behavior varies with the prevalence of that behavior in a person's group.

Several factors may contribute to this phenomenon, as proposed in Manski's (1993) seminal paper. First, and as discussed by Schelling (1971), group composition itself is endogenous: individuals may behave in common ways because they share similar attributes that matter for their decision making. Second, group members are exposed to similar contexts and contextual changes and react to them accordingly. Third and finally, group members may genuinely influence one another, either through their exogenous characteristics—the so-called exogenous effect—or through their actual behavior—endogenous effects. As discussed elsewhere (Manski 1993, 2000; Moffitt 2001; Scheinkman 2008; and others), only endogenous effects are prone to generate the kind of social multiplier that may explain large differences across groups, despite no significant differences in underlying fundamentals. In the present case, we test whether endogenous effects driven by bandwagon effects explain the presence of connected and unconnected clusters within communities, as exemplified in Figure 3.1.

Empirical identification of endogenous effects is prone to a number of identification challenges. One such issue is the so-called reflection problem, formalized in Manski (1993). Accordingly, group behavior being simultaneously influenced by individual behavior, simple linear-in-means models, whereby an individual's action is regressed on the prevalence of this action within the group, cannot distinguish between exogenous and endogenous effects. Nonexperimental solutions have been proposed through the addition of further exclusion restrictions to the model or the reliance on nonlinearities, which allow for multiple equilibria (for example, Brock and Durlauf 2001; Blume and Durlauf 2005). However, these solutions rest on assumptions regarding instruments' validity in the first case and parameter assumptions in the second case, all of which remain weakly testable. Other potential sources of identification rely on models in which one's behavior varies with lagged group outcomes under the assumption that "nonsocial forces act contemporaneously but social forces act on the individual with a lag" (Manski 1993, p540). If such is the case, and if others' exogenous characteristics are themselves constant through time, then one may identify endogenous interactions and corresponding social multipliers.

Finally, promising identification avenues are provided through experimental settings, which exogenously affect either group membership (for example, Sacerdote 2001; Katz, Kling, and Liebman 2001) or the behavior of some individuals within the group (for example, Duflo and

Saez 2003). Our approach is akin to the latter, whereby randomly selected households within village communities were provided discount vouchers as an extra incentive to connect to the electrical grid. In our context, voucher recipients are 18 percentage points more likely to have connected over the course of the study than their fellow villagers who did not win the lottery. The randomness of the voucher allocation ensures its independence from individuals' observable and unobservable characteristics. Our setting is thus one of *partial population experiment,* whereby "there exists an exogenous variable that affects one individual directly but affects the other only through the endogenous social interaction" (Moffit 2001, p59).

A second issue relates to the definition of groups themselves. As reminded by Manski (1993), researchers must first know how individuals form reference groups and perceive reference group outcomes before they can infer social interactions. In this paper, we take a rather exploratory approach to the definition of *reference group*. In short, we investigate the extent to which reference groups evolve with distance. In fact, our data allow us to identify the level of social interactions for various definitions of a geographical neighborhood by changing the distance radius that is considered to select one's neighbors. This, in turn, provides us with a means to assess how social interaction varies with physical distance (see Kremer and Miguel 2007, Dupas 2010 or Devoto et al. 2011 for similar approaches). A caveat, however, is that group membership itself shall not change quickly relative to the influence of social interactions (Moffit 2001). In our case, this means that housing location will not change as a result of group-level connection behavior. The time span of our study is relatively short, however, and it is highly unlikely that housing location changed over the course of the 12 months. A second caveat is that one's reference group may only be partially correlated with the physical distribution of its neighbors, such that our measure is at best a proxy.

We detail our identification strategy in this section. Our purpose here is to estimate how an individual's decision to connect to the electrical grid is influenced by others' decisions to do so. Adapting Manski's (1993) setting to our purpose, our estimation can be described as

$$c_i = \alpha + \beta.\bar{c}_{-i \in d} + z_i{}'\tau + u_i \qquad (1),$$

where c is a binary outcome indicating whether a household has connected to the grid; d characterizes one's reference group, which in this case is a distance radius around one's house; $\bar{c}_{-i \in d}$ measures the proportion of neighbors that have connected to the grid within d meters from one's house; and (z, u) are observable and nonobservable attributes of the household that directly affect y (such as wealth, connection price, and preferences). The parameter β captures endogenous social interactions—namely, the extent to which an individual's connection behavior is influenced by the decision of other households living within a d-meter geographical radius.

As discussed earlier, β may well capture various other reasons that nearby households tend to behave in similar ways (for example, sorting effects, contextual effects, exogenous interactions). If such is the case, a nonzero β will not necessarily be indicative of endogenous social interactions. We therefore use the number of neighbors that have received a voucher as an instrument for the proportion of neighbors that did connect within one's geographic vicinity—indeed, vouchers are a strong, though imperfect, determinant of one's decision to connect. We thus modify equation (1) as follows:

$$c_i = \alpha' + \beta'.\hat{\hat{c}}_{-i\in d} + z_i'\tau' + \varepsilon_{i,} \qquad (2),$$

where $\hat{\hat{c}}_{-i\in d}$ is the predicted proportion of neighbor's connection status from a first stage regression of average connection rate within the radius onto the number of vouchers distributed within this radius.

As discussed in the model above, bandwagon effects operate through time, such that equations (1) and (2) characterize equilibrium results but not the underlying process. To further explore the prevalence of bandwagon effects, we thus propose a lagged interaction model, whereby one's connection decision is driven by the stock of connected neighbors at the previous period. Here again however, the increased proportion of connection rates may relate to other radius-level factors. To account for this, we rely on the voucher-induced exogenous variation in the stock of households connected at a particular time – recall from Table 3.4 Columns (4)-(6) that voucher recipients were likely to connect earlier than non-recipients. In essence, by lowering the cost of connection, the voucher intervention is thus akin to increasing the proportion of always-takers, φ^{AT}, described in the model above, which arguably increases the likelihood of a bandwagon effect onto others. Further, for those 'complier' households in φ^{C}, receiving a voucher entails a lower of the connection threshold θ_i, which characterizes the minimum number of neighbors' connection at previous periods necessary for one to decide to connect. In sum, voucher distribution provides an exogenous variation in the distribution of thresholds, θ_i, to the left. Thus, using the stock of connected voucher recipients within a given vicinity and at a particular time as an instrument for the proportion of connected neighbors within this vicinity at a particular time, we can estimate the following panel model:

$$p(c_{it} = 1 | c_{it-1} = 0) = a + b.\hat{\hat{c}}_{-i,t-1\in d} + \gamma_i + \omega_{it} \qquad (3),$$

where γ_i is a household-level fixed effect.

6. Results

Our estimations rely on two strategies within our dataset. First, we use GPS coordinates to include the connection behavior of an individual's neighbors living within various radiuses of one's home. For each radius, we compute the proportion of connected households and the number of voucher recipients, which allows us to estimate equations (1), (2), and (3) for radiuses varying from 10, 30, 50 and up to 500 meters.

Second, we use connection dates to further expand our dataset through time. In particular, we compute, for various radiuses, the proportion of households that had connected between the date when electricity was available in the community and t periods of 10 days each.[9] Among these, we further computed the number of voucher recipients. The general format of the obtained dataset is summarized in Table 6.1.

[9] Although results are consistent using smaller and larger periods, we use 10-day periods, which is in line with the typical time elapsing between one's demand for connection and the actual connection of one's house.

Table 6.1—Key variables

Time-invariant characteristics	
	Household's socioeconomic characteristics
	Household's connection status at follow-up survey
	Distance to nearest electrical pole
	Household's voucher status
	Number of neighbors that have received a voucher, *within an x distance radius*
	Proportion of neighbors that had connected at follow-up survey, *within an x distance radius*
Time-varying characteristics	
	Household's connection status at time t
	Proportion of connected neighbors at time $t-1$, *within an x distance radius*
	Number of voucher-recipient neighbors that had connected at time t, *within an x distance radius*

Note: Distance radius varies between 10 and 100 meters from one's home entrance.

Results from estimations of equations (1) are reported in Panel 1 of Table 6.2. To keep up with the basic estimate of households' demand for electricity in Section 2, we use the set of baseline covariates—namely, an individual household's consumption and expenditure, age and gender of household head, share of income derived from various sources, voucher status, and distance to the nearest pole. Point estimates for these variables are rather constant and robust across all specifications and not reported here.

Column 1 of Table 6.2 introduces as an additional covariate the number of connected households living within a 10-meter radius of one's home. In Column 2, the radius is increased to 30 meters, and so on until the last column, where we consider a 500-meter radius from one's home.[12] The obtained results are not fully clear, with the only significant and positive correlation found in the smallest radius. Note however that, and argued above, these estimates are likely biased by the various location-specific effects as well as reflection biases. We thus turn to the estimation of equation (2) where the proportion of connected households is instrumented by the number of voucher recipients within the corresponding vicinity.

In Panel 2, we report estimates relating neighbors' connection behavior to the intensity of voucher distribution within an *x*-meter distance radius of an individual's house. Results clearly indicate a strongly significant and positive relationship, although point estimates suggest, as expected, a decreasing correlation between the proportion of households connected and the number of vouchers distributed, as the length of the radius is increased.

[12] The sizes of the radius used were chosen in accordance with the typical dispersion of the population within villages. See for instance the satellite picture presented in Figure 3.1

Table 6.2—Bandwagon effects : Twelve-month estimates

	(1) 10-meter radius	(2) 30-meter radius	(3) 50-meter radius	(4) 100-meter radius	(5) 200-meter radius	(6) 300-meter radius	(7) 400-meter radius	(8) 500-meter radius
	Panel 1. Dependent variable. Household has connected over the course of the study Ordinary least squares (OLS) estimates							
Proportion of connected neighbors within radius	0.369 (0.112)***	0.138 (0.123)	0.128 (0.124)	0.185 (0.131)	0.195 (0.128)	0.205 (0.128)	0.209 (0.128)	0.210 (0.128)
	Panel 2. First stage. Dependent variable. Number of connected neighbors within radius OLS estimates							
# voucher recipients within radius	0.296 (0.023)***	0.065 (0.003)***	0.030 (0.001)***	0.017 (0.000)***	0.015 (0.000)***	0.014 (0.000)***	0.012 (0.000)***	0.010 (0.000)***
	Panel 3. Dependent variable. Household has connected over the course of the study IV estimates with instrument “# voucher recipient within *x*-meter radius”							
Proportion of connected neighbors within radius	0.294 (0.161)*	0.216 (0.126)*	0.229 (0.124)*	0.156 (0.133)	0.159 (0.130)	0.119 (0.137)	0.070 (0.145)	0.017 (0.154)
Observations	134	346	446	537	555	558	558	559

Notes: All estimations within Panels 1 and 3 include the same set of control variables as in Table 3.4, with effects all similar in magnitude and statistical significance. Clustered standard errors are in parentheses. * significant at 10 percent; ** significant at 5 percent, ** significant at 1 percent.
The changes in sample size correspond to observations where no surveyed neighbor was surveyed within the corresponding radius and thus where proportions could not be computed.

We use these results as first-stage in the Instrumental Variable estimation reported in Panel 3. Accordingly, we rely on the strong effect of vouchers on one's decision to connect and the orthogonality of voucher distribution with respect to households' own characteristics and distance from one another, to use the number of neighbors who were endowed with a voucher within a particular radius as an instrument for the proportion of connected neighbors within the same radius. It is worth noting that only 46 percent of voucher recipients had connected at the time of our second survey, whereas 28 percent of the nonvoucher recipients had. This result ensures that the correlation between our instrument and our instrumented variable is strong, though not perfect, further enabling identification. The obtained results give a much clearer picture of the type of bandwagon effects at play. Accordingly, the effect of others' connection behavior onto one's own decision to connect is twice as large when considering a radius of ten meters as compared to a radius of 100 meters. Further, the results display a steady decrease in neighbors influence up to a point where it becomes insignificant.

Finally, Table 6.3 reports estimates of equation (3). Accordingly, we investigate the effect of bandwagon processes through time, instead of at equilibrium. To do so, we use a household fixed-effect panel estimator to assess the probability that one will connect in a given period in response to neighbors' connection behavior in previous periods. Although theoretically better identified than the simple OLS model in Panel 1 of Table 6.2, we further ensure the validity of our estimates by instrumenting neighbors' past behavior by the number of voucher recipients within a given a radius who had connected at a given period. As reported in Panel 1, the first-stage estimates provide strong support for the use of these instruments. Panel 2 reports second-stage estimates; and once again, the results point to a rather clear decreasing influence of neighbors' connection behavior with distance. Note that given the important number of observations where no neighbors were connected at a given time (in early periods essentially), effect in small radiuses are not identified. Yet, as in Table 6.2, the results point toward a convex shape, whereby more neighbors' influence is lost within the first few tens of meters than for farther distances. Quite naturally, these estimates fall below those of the previous tables, with the latter being estimated "at equilibrium"—that is, at the time of the follow-up survey.

Overall, the various estimates clearly support the set hypothesis that neighbors' connection behavior strongly influences the individual's decision, but that such differences significantly decrease with distance from one another. This result, in turn, is in line with our model's prediction that under uneven geographic distribution of houses, one may observe subcommunity cluster effects, depending on the cross-distribution of households' income and physical locations.

Table 6.3—Bandwagon effects through time

	(1) 10-meter radius	(2) 30-meter radius	(3) 50-meter radius	(4) 100-meter radius	(5) 200-meter radius	(6) 300-meter radius	(7) 400-meter radius	(8) 500-meter radius
	Panel 1. First stage. Dependent variable. Proportion of connected neighbors within radius at time $t-1$ Ordinary least squares (OLS) estimates							
# voucher recipients within radius that had connected by time $t-1$	0.798 (0.005)***	0.309 (0.002)***	0.125 (0.001)***	0.056 (0.000)***	0.034 (0.000)***	0.024 (0.000)***	0.019 (0.000)***	0.017 (0.000)***
	Panel 2. Dependent variable. Household connection status at time t, given no connection at $t-1$ IV estimate with instrument "# neighbors connected with a voucher within x-meter radius"							
Proportion of neighbors connected before, within radius	. .	0.035 (0.032)	0.072 (0.029)**	0.047 (0.011)***	0.044 (0.006)***	0.039 (0.005)***	0.039 (0.005)***	0.036 (0.005)***
Observations	.	3,109	5,400	10,138	12,697	14,338	14,939	15,464
Number of households	.	119	187	307	404	463	493	516

Notes: Robust standard errors are in parentheses. * significant at 10 percent; ** significant at 5 percent, *** significant at 1 percent
The changes in sample size correspond to observations where no surveyed neighbor was surveyed within the corresponding radius and thus where proportions could not be computed.

To further ensure that the estimates do in fact capture social comparisons-based bandwagon effects, one needs to rule out alternative explanations. First, one could argue that nearby households share fixed connection costs, whereby one's house is electrified through EEPCo (the electric utility), and neighbors later connect to it informally. This effect is akin to what Manski (2000) referred to as *constraint interactions;* it is, in fact, a rather common observation in many developing countries and is often referred to as spiderweb electrical connections. In the present context, however, such features were not observed, not the least because an EEPCo office was permanently installed in each community to provide connections and prevent illegal ones. Alternatively, one could imagine that one's connection entails negative externalities on others if, for instance, visitors would converge towards electrified houses and no longer to the non-electrified ones. Yet, with limited effects found on electrified households' time allocation and in particular on time spent entertaining visitors, such effects are unlikely. Finally, one could argue that positive externalities exist, whereby one's connection to electricity also benefits others (kids could go study into the neighbors' electrified house, or one could recharge her cell-phone using her neighbor's connection). While we cannot rule out such effects, their presence would imply a negative relationship between one's probability to connect and her neighbors' connection status, such that our effects constitute a lower bound on the effective positive influence.

Second, such endogenous social interactions could be driven by expectations interactions, whereby neighbors influence an individual's connection rates by releasing information on the benefits of connection once they connect. In our case, however, such social learning seems unlikely, given households' high initial knowledge of the advantages and disadvantages of electricity, as revealed in Table 3.1. Yet, to further rule out such explanations, Table 6.4 provides similar estimates as those of Table 6.2, but this time splitting the sample between the 66 percent subset of households that answered "strongly agree" to all statements displayed in Panel 1 of Table 3.1, and the other ones (most of whom answered positively to a majority of these statements). Accordingly, lower estimates would indicate that at least part of the social interaction observed is due to such social learning phenomenon. Our results suggest, however, greater point estimates on those well-informed neighbors, suggesting that social learning, if present, plays a marginal effect. On the contrary, we find no effect on the sample of less-informed households, effectively suggesting that little social learning is at play.

Table 6.4—Ruling out social learning

	(1) 10-meter radius	(2) 20-meter radius	(3) 50-meter radius	(4) 100-meter radius	(5) 200-meter radius	(6) 300-meter radius	(7) 400-meter radius	(8) 500-meter radius
	Panel 1. Dependent variable. Household has connected over the course of the study Sample restricted to households with highest perception of the benefits of electrification at baseline IV estimates with instrument "# voucher recipient within *x*-meter radius"							
Proportion of neighbors connected within radius	0.501 (0.160)***	0.569 (0.156)***	0.486 (0.199)**	0.374 (0.240)	0.290 (0.253)	0.124 (0.304)	-0.043 (0.366)	0.185 (0.425)
Observations	89	227	293	354	365	368	368	369
	Panel 2. Dependent variable. Household has connected over the course of the study Sample restricted to households with lower (although still high) perception of the benefits of electrification at baseline IV estimates with instrument "# voucher recipient within *x*-meter radius"							
Proportion of neighbors connected within radius	-0.019 (0.325)	-0.031 (0.166)	0.044 (0.157)	0.033 (0.173)	0.095 (0.167)	0.077 (0.171)	0.062 (0.176)	0.030 (0.181)
Observations	45	119	153	183	189	190	190	190

Notes: All estimations include the same set of control variables as in Table 3.4, with effects all similar in magnitude and statistical significance. Robust standard errors are in parentheses. * significant at 10 percent; ** significant at 5 percent, *** significant at 1 percent.

Finally, as in any experimental study, voucher distribution could lead to a community-level tendency toward connection. Yet, there is no reason a priori for such effects to be clustered within the community. In addition, if vouchers had an effect on an individual's connection other than through the face value of the vouchers, one would expect to find that the price elasticity of connection through voucher-based reductions differs from the standard price elasticity of connection. To further assess these issues, we report in Table 6.5 the price elasticities estimated through a series of contingent valuation questions. For each nonconnected household, we asked during the second-round survey whether they would have connected had the price been *p*, with *p* chosen to be below the minimum price of connection for a household and randomly varied across all nonconnected households.

Table 6.5—Price elasticities of connection

	(1) Dependent variable. Would have connected had price been *p*	(2) Dependent variable. Did connect over the course of the study
p	–0.137	
	(3.21)**	
Received a 20% discount voucher		0.142
		(2.96)**
Distance to nearest pole	0.001	–0.001
	(4.28)**	(3.85)**
Consumption expenditures (*1,000 ETB)	0.016	0.016
	(2.74)**	(2.38)*
Age of household head	–0.001	0.003
	(0.36)	(1.60)
Gender of household head (1 = male)	0.168	0.205
	(2.49)*	(3.26)**
Household size	0.009	0.012
	(0.91)	(1.13)
% income from self-employed agriculture	–0.001	0.001
	(0.60)	(0.84)
% income from self-employed nonagriculture	–0.000	0.003
	(0.10)	(2.35)*
% income from trade activities	0.002	0.003
	(0.97)	(1.74)
% income from salaried activity	0.001	0.003
	(0.70)	(2.52)*
Observations	274	387

Notes: Robust *t* statistics are in parentheses. * significant at 5 percent; ** significant at 1 percent.

Results from a simple OLS estimation in Column 1, where the dependent variable is the households' decision to connect if price had been *p* and *p* is the independent variable, show a negative price elasticity of one's decision to connect of about 13 percent for each increase of 100 ETB in the connection price. In Column 2, we report the elasticity of connection with respect to vouchers. With average connection costs of about 500 ETB, we restrict the sample to the recipients of a 20 percent voucher discount, so that the obtained coefficient can be interpreted as a 100 ETB discount on price, which is easily comparable with results in Column 1. As displayed, results are clearly similar in magnitude, ruling out the hypothesis of an experimental bias in the results obtained earlier.

7. Conclusion

Recent research in social psychology emphasizes the role of *descriptive social norms*, whereby individual decisions are strongly influenced not just by what others may approve of but also by what others actually do. This influence is further reinforced if one sees commonalities between one's own characteristics and those of others (for example, Goldstein, Cialdini, and Griskevicius 2008). Thus, visibility of others' consumption patterns bears important policy implications on the adoption of particular actions that carry positive externalities. This may for instance be the case if one wishes to promote environmentally friendly behavior (Chenevix-Trench 2008).

This paper provides indirect evidence that such effects may be quite prevalent, even in poor settings, such as in rural Ethiopia, and even for expensive goods, the consumption of which may require the eventual sacrifice of more basic necessities. Despite their potential importance for the design of economic policies in such settings, social comparison-driven bandwagon effects on consumption, technology adoption, or program participation have so far received attention only in the theoretical literature; they have received little empiric attention, least of all in developing countries. One reason for this gap lies with the difficult identification of such social comparison–based mechanisms. Using the example of connection to a newly installed electrical grid and an appropriate data collection effort, our results show that an individual's connection decision is strongly influenced by decisions of the individual's nearest neighbors, and less influenced by those living farther away.

Interestingly, these results are very much in line with Devoto et al. (2011) study, which shows that connection to piped water in urban Morocco is in part determined by neighbors' connection, and that these effects decrease with neighbors distance from one another. In this study, the authors conclude to an *expectation interaction* type of effect whereby connected households would tell their friends "how happy they are with they are about the connection", although no particular data are presented to sustain this interpretation. The present paper faces the same difficulty in directly testing for *preference interactions*, although a number of indirect evidence provides significant support to it. To further explore these mechanisms, future research should therefore aim at collecting data on households' decision-making in relation to others. As argued in Manski (2000), this may however require that more qualitative approach be implemented alongside standard household surveys.

In turn these studies could help inform policy decisions in a meaningful way. For instance, recent debates on so-called *smart subsidies* propose that consumption subsidies for promoted goods should be specifically targeted to those households that cannot afford the good's face value. Yet other evidence suggests that even when such items as deworming pills are given for free, take-up remains low in developing countries (Kremer and Miguel2007). Recent studies have highlighted the role of learning from other types of mechanisms, whereby information exchanges and observation of others' actions are used to assess the benefits of a given technology (for example, Oster and Thornton forthcoming) or to influence participation in a program such as microcredit (Banerjee et al. 2011). Yet, if "keeping up with neighbors" types of mechanisms are also at play, appropriate targeting, along with enhanced visibility of consumption, may induce the type of bandwagon effects that could enhance adoption rates of various human capital–related or other socially desirable technologies.

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