Social Learning among Urban Manufacturing Firms: Energy-Efficient Motors in Bangladesh*

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Jan. 2025

PRELIMINARY — PLEASE DO NOT CIRCULATE

Abstract

Knowledge spillovers among firms have long been seen as central to the growth and development process but are difficult to estimate cleanly. We randomly allocated an energy-efficient motor – called a servo motor – among leather-goods firms in Dhaka, Bangladesh and tracked adoption, beliefs about energy savings, and willingness to pay for the new motor. We find robust evidence of spillovers from nearby firms on adoption behavior. We find little evidence of spillovers within firms' communication networks. A marginal value of public funds (MVPF) calculation taking learning spillovers into account yields a significantly larger value than one that only considers reduced electricity usage by treated firms and suggests that subsidizing adoption of servo motors would be a relatively cost-effective policy intervention.

* We are grateful to the Information for Development Program Multi Donor Trust Fund (InfoDev MDTF), the King Climate Action Initiative of J-PAL, the International Growth Centre, the Private Enterprise Development in Low-Income Countries (PEDL) initiative, the Alfred P. Sloan Foundation (G-2023-21088), and the Templeton World Charity Foundation for funding. We thank Susanna Berkouwer, James Berry, Florian Grosset-Touba, Fahad Khalil, Urmee Khan, Atonu Rabbani, Esteban Rossi-Hansberg, Cyrus Samii, Panos Toulis, and several seminar participants for helpful comments. Yunfan Gu was initially involved in the project and made valuable contributions in the early stages. The project was carried out in collaboration with the IPA Bangladesh office. Project manager Ijaz Khan and research associate Ahnaf Habib were invaluable. We also benefited from excellent research assistance by Jing (Piper) Wang, Taha Barwahwala, and Syful Hoque. The AEA RCT Registry ID is AEARCTR-0007432. All errors are ours.

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1 Introduction

Knowledge spillovers among firms have long been seen as central to the industrial development process. They have played a key role in economists' thinking about agglomeration (Marshall, 1890; Jacobs, 1969; Glaeser et al., 1992; Henderson et al., 1995; Davis and Dingel, 2019) and growth (Romer, 1986; Lucas, 1988; Aghion and Howitt, 1998; Hausmann and Rodrik, 2003; Acemoglu, 2009). Knowledge spillovers are especially salient when they involve energy-efficient technologies. Adoption of such technologies may generate two externalities — a climate externality and a learning externality — which give rise to two market failures (Jaffe et al., 2005; Popp et al., 2010; Gerarden et al., 2017). Understanding these dual market failures and how they interact is crucial for the design of effective policies to reduce emissions and mitigate climate change.

Knowledge spillovers are also difficult to estimate empirically, especially among urban manufacturing firms. There are several related challenges. One is the familiar issue that correlated unobservables may lead firms to make similar technology decisions even in the absence of learning effects, well known since the work of Manski (1993). A second challenge is measurement: datasets on manufacturing firms rarely contain direct information on the technologies being used, and researchers have often had to rely on residual-based measures of productivity, which are subject to many different interpretations. A third challenge is that a common approach to estimating spillovers — a saturation design with varying intensity of treatment across a large number of independent clusters — is unlikely to be available, since few industries have enough clusters of firms using similar technology to permit statistical inference, and if such an industry existed it is unlikely that information flows across clusters would be ignorable.

In this paper, we present the results from an experiment among leather-goods producers in Dhaka, Bangladesh, in which we randomly allocated energy-efficient motors — called servo motors — for stitching machines. The servo motors can be swapped seamlessly for traditional "clutch" motors on existing machines — a fact that was not widely known —– and require no other changes in production processes. Our research design allows us to address the three challenges highlighted

in the previous paragraph. First, the experiment generates clearly exogenous exposure to the technology. Second, we observe directly whether firms adopted the motors, as well as information flows between firms, managers' beliefs about energy savings, and managers' willingness to pay for the motors. Third, applying recent methodological advances on estimation in the presence of interference across units, we are able to separately estimate direct treatment effects and spillovers in a single network.

Our experiment has three arms. In the first arm, which we refer to as the "information only" arm and label T1, we provided a video about servo motors, explaining the cost savings and showing how to replace a clutch motor with a servo motor on an existing machine. In the second arm, which we refer to as the "information and installation" arm and label T2, we installed a servo motor on one machine and electricity meters on two machines, one with the new servo motor and one with a clutch motor. In this arm, we also gave firms reports showing the electricity usage per hour of the two machines with meters, side by side. A third arm, labelled C, served as control. As explained below, we implemented the treatments in a somewhat non-standard way, by varying the underlying price distributions in a Becker, DeGroot and Marschak (1964, hereafter BDM) procedure to elicit firms' willingness to pay for a new motor. To be included in the randomization sample, firms had to have at least two machines with clutch motors and to pay for their electricity on a per-unit basis. Using these criteria, there were 505 firms in the randomization sample, which we divided equally among the three arms.[1]

To estimate the direct effects and spillover effects of the treatments simultaneously, we apply the "re-centering" approach of Borusyak and Hull (2023). The key step is to construct a measure of expected exposure to a treated firm, and to use the difference between actual exposure and expected exposure to identify the effect of exposure. As measures of exposure, we primarily use indicators for whether there were any T2 firms within a given distance or within a firm's com-

[1]We implemented two cross-cutting interventions, with incentivized belief elicitation for some firms in all three arms and electricity meters on clutch motors for some T1 firms. These interventions had little effect and we pool firms in the three main arms in our baseline results, with caveats we discuss below.

munication network; we explore robustness to alternative measures of exposure. To calculate expected exposure, we simulate a large number of counterfactual treatment assignments and take the mean exposure across simulation draws. Expected exposure thus captures the fact that some firms are more central in networks than others, for instance because they are located near many other firms or have more business contacts.

Our baseline specification is a regression of adoption of a new servo motor on treatment indicators, exposure within a very local area, and expected exposure (as well as neighborhood effects and stratum effects, as explained below). In our preferred specification, we define exposure as having any T2 firm within a 500 meter radius, although we show that the results are robust to using different distances. The key finding is a robust positive impact of very local exposure on servo motor adoption: a firm exposed to at least one T2 firm within 500 meters, controlling for expected exposure within this distance, is 16-19 percentage points more likely to adopt at least one new servo motor than a firm without such exposure. We also find direct impacts of the two treatments, T1 and T2. The effect of T2 on the first new servo motor adoption is mechanical but we also find a significant, non-mechanical effect of 9 percentage points on what we refer to as "intensive adoption" — adoption of servo motors beyond the one provided in the experiment. We also find a modest positive impact of 9-10 percentage points of T1, the information-only treatment, on adoption. Comparing the magnitudes of the information-only (T1) effect and the spillover effect, it is striking that having a T2 firm nearby has a larger impact than directly receiving information about servo motors in video form.

We explore a number of other dimensions of the social learning process. We examine how adoption responds to exposure to at least one T2 firm in a firm's communication network (the set of business contacts reported by the firm at baseline) and find, perhaps surprisingly, little evidence of spillover effects through this channel. We discuss possible explanations, including that firms are reluctant to share information about new technolgies with competitors. We also examine impacts on managers' beliefs about energy savings from servo motors and on their willingness to pay for servo motors. We find that T2 moves beliefs in the

expected direction, but we find little impact of T1 on beliefs or of exposure to a nearby T2 firm on beliefs. It appears that some firms are spurred to adopt servo motors by our video or local exposure even before being fully convinced of their energy benefits. For willingness-to-pay, we find effects of T1 and T2 in the expected direction, but, again, little evidence of spillover effects. We also use the rich data we have collected to understand the mechanisms underlying the local spillovers we observe. We find, for instance, that if a firm is exposed to a T2 firm within 500 meters, the manager of the firm is more likely to pray at the same mosque as the manager of a T2 firm; this is a possible channel of information flows.

A natural question in this context is to what extent governments or philanthropists should be willing to subsidize the adoption of servo motors. If we focus solely on the reduction of emissions from the energy savings of servo motors, using current estimates of the Social Cost of Carbon (SCC) but ignoring the knowledge spillovers that adoption generates, then subsidizing servo motor adoption is not a particularly cost-effective way to reduce carbon emissions. But if we take both the climate extenality and the learning externality into account, then such subsidies are revealed to be a much more attractive intervention. To quantify the benefits, we calculate the Marginal Value of Public Funds (MVPF) following the approach of Hendren and Sprung-Keyser (2020) and in particular the extension of Hahn et al. (2024), who show how to incorporate learning effects into MVPF calculations. Taking into account both emissions externalities and learning externalities, we arrive at an MVPF of 7.7. Comparing MVPFs for 96 environmental policies studied over the past 25 years, Hahn et al. (2024) consider an MVPF greater than 5 to be large. While an MVPF of 7.7 is not the largest among the interventions they consider, it appears that subsidizing servo motors legitimately deserves attention as an environmental policy intervention.

Beyond the studies cited above, our paper is related to several literatures. It is perhaps most closely related to the literature on local knowledge spillovers within cities. Among advertising agencies in southern Manhattan, Arzaghi and Henderson (2008) find that there is a profit benefit to locating very near other agencies which decays quickly with distance beyond 250 meters. Using cell-phone records

in Silicon Valley, Atkin et al. (2022) estimate the importance of face-to-face meetings for innovation, as evidenced by patent citations across firms. Rosenthal and Strange (2020) provide a review of work in this area. Relative to this literature, the main distinctive aspects of our study are, first, that we have a randomized experiment (and do not need assumptions about exclusion restrictions as in the instrumental-variables papers in the aforementioned papers) and, second, that we focus on spillovers about production technologies, which we believe are important in their own right.

There is a small experimental literature on knowledge spillovers among non-agricultural firms. Two leading papers in this literature address the Manski (1993) issue by manipulating firms' networks. Fafchamps and Quinn (2018) put entrepreneurs together to judge business-plan competitions and find some evidence of spillovers on tax registration and having a bank account but not on management practices or innovation. Cai and Szeidl (2018) induced firms to attend monthly meetings and find large effects on firm performance and, notably, flows of information about a savings opportunity and a government grant among members of the groups, with evidence of less sharing of "rival" information. Relative to these studies, a distinctive aspect of our paper is that we focus on a naturally occurring production technology and how it diffuses in existing networks. The consideration of the role of distance in an urban setting is also a differentiating feature.[2]

There is a larger non-experimental literature on social learning by non-agricultural firms. Notable contributions in this area include Irwin and Klenow (1994), Thornton and Thompson (2001), Greenstone et al. (2010), Bloom et al. (2013), Bloom et al. (2019), Alfaro-Ureña et al. (2022), and Myers and Lanahan (2022). The experimental variation in our setting is an advantage relative to this literature.

There is a substantial literature on social learning in agriculture in developing countries, much of it experimental, reviewed by Magruder (2018) and Suri

[2]Relatedly, Hardy and McCasland (2021) randomly allocated training in a new weaving technique and randomly placed orders for garments using the technique among small Ghanaian garment producers. Consistent with Cai and Szeidl (2018), they find that firms are more likely to share information when they are not in competition. They do not focus on diffusion along pre-existing network links. A contemporaneous paper by Houeix (2025) focuses on diffusion of a digital-payment technology among taxi drivers and owners in Senegal.

and Udry (2022). In a seminal study of pineapple growing in Ghana, Conley and Udry (2010) collected information separately on information networks (whom people talk to) and geographic networks (who their neighbors are) and find that surprising success in growing pineapples by members of a farmer's information network is associated with greater adoption of pineapple production, especially if it is by veteran farmers or farmers of similar wealth level. Other notable contributions include the experimental studies of Hanna et al. (2014), Beaman et al. (2021), BenYishay and Mobarak (2019), Meriggi et al. (2021), Duflo et al. (2023), Patel (2024), and Cefalà et al. (2024). We believe that social learning among urban manufacturing firms is of inherent interest, because of such firms' importance for economic growth and climate mitigation. Our setting also has study-worthy features that are often absent in agricultural settings: imperfect competition among producers, which may generate an incentive to hide information, and intense concentration of producers in a small geographic area, which may make very local spillovers particularly salient.

Our paper is also related to a literature in environmental economics on the adoption of energy-efficient technologies, which includes Anderson and Newell (2004), Allcott and Rogers (2014), Newell and Siikamäki (2014), Newell and Siikamäki (2015), Allcott and Taubinsky (2015), Ryan (2018), Berkouwer and Dean (2022), and Brooks et al. (2024).[3] Much of this work has focused on households, rather than firms. Also, few studies have focused on learning spillovers. In a recent review, Gerarden et al. (2017, p. 1490) write, "We are not aware of any direct empirical evidence of [learning-by-doing] in energy efficiency, and none about the extent of any learning spillovers." One goal of our paper is to fill this gap.

Our paper is also related to studies estimating spillover effects in other contexts. Duflo et al. (2008) highlight three broad approaches: the saturation designs mentioned above (see e.g. Duflo and Saez (2003), Crépon et al. (2013), Baird et al. (2018)); experimental manipulation of networks, as in Fafchamps and Quinn (2018) and Cai and Szeidl (2018); and using the variation generated by randomization, controlling for expected exposure, as in Miguel and Kremer (2004). Our study falls in the third category; the Borusyak and Hull (2023) re-centering ap-

[3]For reviews, see Allcott and Greenstone (2012) and Gerarden et al. (2017).

proach can be understood as an analogue of the Miguel and Kremer (2004) approach of controlling for the density of schools nearby.

The next section describes our setting and Section 3 describes the experiment. Section 4 discusses our econometric strategy. Section 5 presents the results. Section 6 considers mechanisms through which proximity may affect adoption. Section 7 considers the social benefit of subsidies to servo motor adoption. Section 8 concludes.

2 Setting

2.1 Dhaka Leather-Goods Sector

The two main categories of goods in the leather-goods sector in Dhaka are bags (and accessories such as wallets and belts) and footwear. Both categories have different product varieties, which can be loosely sub-categorized as basic (e.g., carry bags, wallets, sandals, slippers), fashion-oriented (e.g., sling bags, vanity bags, oxford shoes, derby shoes), or related to sports and other specific purposes (e.g., travel bags, sports bags, running shoes, water sports shoes).

The firms in our sample are largely organized in clusters that are geographically concentrated. They are spread over the Dhaka Division (a rough analogue to Metropolitan Statistical Area in the Bangladeshi context), which comprises the Dhaka district and Kishoreganj district. Approximately 90% of our sample is in the Dhaka district where firms belong to one of three dense industrial clusters: *Kamrangirchar*, *Hazaribagh*, and *Bangshal*.[4] (See Figure 1.) The geographical proximity of firms is best illustrated in the *Bangshal* area of old Dhaka where factories are often located on different floors within the same building. (See Figure 2.)

[4]These areas are officially referred to as thanas under the Dhaka City Corporation but function like sub-districts (*upazilas*). Kishoreganj district includes the sub-districts of *Bajitpur* and *Bhairab*.

2.2 Electricity Generation in Bangladesh

Bangladesh relies heavily on fossil fuels for electricity generation. In 2021, only around 1% of Bangladesh's electricity was generated from renewable energy sources such as hydro, solar, and wind. Natural gas accounted for 73.1% of the electricity generated in the country. The corresponding shares of oil and coal were 20.1% and 5.5% respectively (IEA, 2023). Unreliable electricity grids also result in the use of diesel-fueled backup power generators (Tong and Zhang, 2015).

The consumption of electricity is effectively subsidized in Bangladesh. In the 2022-2023 fiscal year, the cost of generating electricity for the Bangladesh Power Development Board (BPDB), the state-owned electricity utility, was 11.3 Bangladeshi Taka (BDT) per kilowatt-hour (kWh).[5] The BPDB also acquired electricity from independent producers (which constituted 63% of the total electricity supply) at 14.6 BDT per kWh. The average price paid by firms in our sample was 12.5 BDT per kWh, above the BPDB's own marginal cost of electricity but below the independent producer price. The BPDB also incurs substantial fixed costs which are covered by the government. In the 2022-23 fiscal year, the government provided a subsidy of more than 395.35 billion BDT. In short, the price that would allow BPDB to break even was well above the 12.5 BDT per kWh paid by firms in our sample. In 2023, under pressure from the IMF, the government raised electricity prices at the retail level in three consecutive months – January, February and March – by around 5% each month (Byron, 2024), but price remain well below average production cost.

The social cost of producing electricity is even higher, given carbon emissions. While it is estimated that natural gas emits 50 to 60 percent less carbon emissions when combusted in a new, efficient natural gas-power plant compared with emissions from a typical new coal plant (U.S.EIA, 2023), the power generation sector is still a major source of growing emissions in Bangladesh. In 2021, electricity production accounted for 56.1% of the country's carbon emissions. In terms of the end users of electricity, the industrial sector accounted for 42.9% of the total final consumption of electricity in Bangladesh (IEA, 2023).

[5]The exchange rate over our study period was approximately 100 BDT/USD.

2.3 Servo vs. Clutch Motors

Figure 3 shows photos of a clutch motor and a servo motor. Traditional clutch motors work by magnetic induction: an electrical current passes through an outer chamber and creates a rotating magnetic field, which leads a rotor to spin, which (when the clutch is engaged) powers the movement of the needle. It takes time to generate the rotating magnetic field; the motor needs to "warm up." As a result, machine operators typically leave the motor on even when the needle is not moving. It is estimated that the needle moves only about one-third of the time a worker is sitting at the machine. Hence a significant share of the energy use of a clutch motor is from idling. In contrast, servo motors have a powerful magnet built in. There is no "warm up" period; the motor requires electricity only when the needle is moving.

Using data collected in our experiment (described in more detail below), we calculate that a machine with a clutch motor consumes 0.064 kWh per hour of use, while a machine with a servo motor consumes only 0.019 kWh per hour. This represents a 71% reduction in electricity consumption — roughly equal to the 75-80% reduction that producers of servo motors claim in their marketing materials. The local market cost of the new servo motor used in our experiment is 4,600 BDT (approximately USD 46). Given a mean electricity prices of 12.5 BDT/kWh and assuming that a stitching machine is used for 160 hours per month, we calculate that switching from a clutch to a servo motor reduces electricity costs by 90 BDT (approximately USD 0.90) per month. This implies a payback period of 51 months. While this implies a respectable return on investment of 23.4% per year (12*.9/46), the payback period is longer than the rule-of-thumb cutoffs that many firms, even in the U.S., use to make technology decisions (Anderson and Newell, 2004).

Servo motors are standard equipment on most new sewing machines. But there are many older machines with clutch motors still in use in the Dhaka leather-goods sector. Servo motors can be swapped seamlessly for clutch motors on existing machines. It appears that this fact was not widely known. At endline, 73% of firms said that they learned that a servo motor could replace a clutch motor on an existing machine from our intervention.

3 Experiment

3.1 Sample

We conducted two listing exercises to find firms suitable for our experiment: a phone survey and a door-to-door survey. The phone survey was conducted in two phases between May and August 2021. (We had initially planned to do only a door-to-door listing exercise but had to start with a phone survey due to COVID lockdowns.) We used multiple datasets to get a list of firm phone numbers for the phone listing exercise.[6] We also conducted snowball sampling from this list. After the phone listing survey, when the COVID situation improved in Bangladesh, we conducted a door-to-door listing survey in Dhaka and Kishoreganj districts in September-October 2021.

To be included in our sample, we required that leather goods and footwear firms (i) have at least two stitching machines with clutch motors, (ii) have a separate electricity meter, and (iii) pay an electricity bill on a per unit basis.[7] Our initial list consisted of 625 firms for the baseline survey. Of these, 95 firms were dropped before our next visit because they were closed or no longer met the study criteria.[8] Another 25 declined to participate in the experiment. There were thus 505 firms in our randomization sample. Of these, 473 firms continued to participate until the endline.[9]

We conducted the baseline survey in April 2022. We conducted elicitations of willingness-to-pay (WTP) for servo motors and beliefs about electricity consumption by servo and clutch motors (described in more detail below) in a second visit in Oct.-Nov. 2022; we call this the "initial BDM visit." We conducted a

[6]The datasets are: the 2013 Bangladesh Economic Census 2013, the 2013 and 2019 Bangladesh Business Directories, and member lists of the Leather Goods and Footwear Manufacturers and Exporters Association of Bangladesh, Sports Shoes Manufactures and Export Association, Bangladesh Paduka Prostutkarok Samity, Bhairab Footwear Factory Owners' Association, and the Bangladesh Finished Leather, Leather Goods and Footwear Exporters' Association.

[7]For requirements (ii) and (iii), it was sufficient to have a "sub-meter" installed by their landlord and pay the latter on a per unit basis. Firms that paid their landlords a fixed amount for electricity did not meet our eligibility conditions.

[8]47 firms had shut down, 31 did not have at least two clutch motors, 14 did not have a separate electricity meter and 3 did not get an electricity bill on a per unit basis.

[9]With the exception of one refusal at midline, all attrition between the second visit and the endline was due to firm closures.

midline survey in April 2023 and an endline survey in Oct. 2023.

3.2 Treatment Arms

There were three main treatment arms: information only (T1), information and installation (T2), and Control (C). Assignment to the arms was carried out through the BDM procedure described in Section 3.3 below. Here we describe the content of the information provided.

3.2. 1 Information-Only Arm

Firms in T1 were provided detailed information about servo motors in a 5-minute video shown on a tablet. The video showed servo motors in operation in firms similar to those in our sample. It explained that servo motors use 75% less electricity than clutch motors and walked through a calculation of electricity costs for machines with servo and clutch motors. The video also explained that clutch motors can be easily replaced by servo motors in around 15-20 minutes using ordinary tools and showed a step-by-step demonstration of the replacement procedure.

As noted above (footnote 1), we subdivided this treatment arm into two groups. In the first subgroup (labelled T1a), we only showed firms the informational video. In the second subgroup (labelled T1b), we showed firms the video and installed an electricity meter on a stitching machine with a clutch motor. The meter displayed and stored electricity usage on the specific machine on which it was installed. Every month we collected this information. Between January and June 2023, we provided firms with monthly reports about electricity usage on the metered machine. The intent behind the T1b reports was to examine whether making electricity consumption by stitching machines more salient – while not explicitly comparing it across clutch and servo motors– has an impact on beliefs and adoption.

3.2. 2 Information and Installation Arm

Firms in T2 were given a more intensive information intervention. Through the BDM procedure described below, we replaced a clutch motor with a servo motor on one stitching machine. We asked T2 firms to show us their two most used clutch motor machines and, with their consent, randomly picked one of those machines for servo motor installation. We also installed electricity meters on both machines, the machine with the new servomotor and the other machine (not selected for the servo motor).

As for subgroup T1b, we provided monthly reports to T2 firms based on monthly meter readings between January and June 2023. For T2 firms, each report showed (i) the past month's total electricity consumption, (ii) total hours of usage, and (iii) average electricity consumption per hour for the recipient firm's meter-equipped clutch and servo motor machines. The recipient firm could easily compare electricity usage on its clutch and servo machines by looking at the report. Each T1b report contained the same summary statistics, but only for the recipient firm's meter-equipped clutch motor machine. Figure 4 presents two examples of the reports given to T2 firms. (The reports for the T1b subgroup were similar but only included the blue bars for the clutch-motor machine.)

3.3 Eliciting Willingness to Pay

We elicited managers' willingness to pay for a servo motor through a Becker-DeGroot-Marschak (BDM) procedure along lines that have been widely used elsewhere (see e.g. Berry et al. (2020)). Respondents were first provided with a receipt for BDT 10,000 (USD 100) and informed that they would receive this "incentive amount" in their mobile money account if they fully completed the exercise. They were also informed that if they purchased a servo motor in the exercise, we would reduce the incentive amount by the price of the servo motor. Because we could not carry out the BDM procedure with a respondent who was completely uninformed about servo motors, we provided all respondents with a one-page brochure with an image of a servo motor and the following text: "A servo motor is a modern type of motor, and it can replace a clutch motor on a stitching machine

easily."

We elicited respondents' willingness to pay for a servo motor through an ascending-auction format: we stated a very low price and asked if they would be willing to purchase the item at that price; if the respondent said yes, we raised the price in small increments until they said no.[10]

We then presented the respondent with a bag, explained that it contained chits with random prices for the product, and asked them to pick a chit from the bag. If the price drawn from the bag was equal to or lower than the respondent's stated maximum price, then the respondent received the servo motor at the price displayed on the chit and we reduced the incentive payment by that price. If the respondent's maximum price was lower than the price on the chit, then he or she did not receive the servo motor and received the full 10,000 BDT incentive payment. The distributions of prices in the bags of chits varied by treatment group, as described below. When conducting the exercise, we informed respondents about the support of the distribution, which was between 0 and 10,000 BDT, but we did not state the distribution itself.[11]

We conducted the BDM exercise with every firm in the study three times, at the initial BDM visit, during the midline survey, and during the endline survey.

3.4 Eliciting Beliefs about Electricity Usage

In the belief-elicitation exercise, we asked managers to imagine a firm similar to theirs and to state their beliefs about the following:

1. The number of units of electricity (in kWh) used in an average day with an eight-hour shift and normal scheduled break by a typical sewing machine with a clutch motor.

2. The number of units of electricity (in kWh) used in an average day with an

[10] We chose this ascending auction format because our field tests suggested that respondents would find it easier to comprehend than the more traditional BDM approach of just asking them to state a maximum price on a continuous scale. Burchardi et al. (2021) compare the ascending auction format with the traditional alternative and find that they perform similarly. Before asking about prices for the servo motor, we did a practice round with a small item (a pen).

[11] In a related BDM exercise, Burchardi et al. (2021) vary whether the distribution is stated or unstated to respondents and find that it does not affect bids.

eight-hour shift and normal scheduled break if that clutch motor were replaced by a servo motor.

3. The price paid per unit of electricity (BDT per kWh).

On a tablet, we divided the range of possible answer values into ten bins and asked respondents to allocate 10 matchsticks among those bins. We explained that each matchstick represented a 1 in 10 chance, and that adding a matchstick to a bin meant that they thought the true answer was more likely to lie within that bin. Procedures of this type have been extensively used in field studies (Delavande et al., 2011).

To understand whether incentives improve respondents' answers, we implemented a cross-cutting randomization, with half of our sample in each treatment group participating in an incentivized belief-elicitation exercise and half in a non-incentivized one. Incentivized approaches are common in experimental economics (Schotter and Trevino, 2014; Schlag et al., 2015) but have not been used as frequently by development economics practitioners (Delavande et al., 2011). In the incentivized exercise, the reward for how close the response was to the true answer was determined by the Quadratic Scoring Rule (QSR), a commonly used method in experimental economics. It is suitable for eliciting entire distributions (as we have done) and belongs to the class of scoring rules that induce subjects to report their true subjective beliefs (Schotter and Trevino, 2014).[12] Respondents in the incentivized exercise were informed that the reward would be disbursed to them after the endline survey.

The belief-elicitation exercise was conducted using a tailor-made tablet-based application. Figure 5 presents screenshots of the app interface for the incentivized group. On this app, respondents could allocate matchsticks to the bins using a drag-and-drop feature. Once all 10 matchsticks were allocated, a table appeared showing the 10 potential reward amounts from that allocation (each conditional on one of the 10 bins being correct). This table updated as the allo-

[12]To be precise, the QSR induces subjects to report their true subjective beliefs if (a) individuals are expected utility maximizers, and (b) they are risk-neutral (Schotter and Trevino, 2014). Harrison et al. (2017) show that the bias from risk-aversion is small in practice when eliciting belief about a full distribution, as we have done.

cation changed, allowing the respondent to see in real-time how their potential reward varies as they adjust the allocation.

As for the BDM exercise, we conducted the belief elicitation with every firm at the initial BDM visit, midline survey, and endline survey.

3.5 Randomization Procedure

We embedded the randomization into the baseline BDM procedure by varying the distribution from which the BDM price was drawn across the treatment arms. For the control arm, the baseline BDM price was drawn from a right-skewed distribution, with almost all prices near the maximum of the support of the distribution (10,000 BDT). As a result, the BDM price was almost always above the stated baseline WTP, and almost no control firm purchased the servo motor after the baseline WTP elicitation. Similarly, the baseline BDM price for T1 was drawn from a right-skewed distribution, ensuring that almost no T1 firm purchased the servo motor after the the baseline WTP elicitation. For the T2 arm, we drew the BDM price from a left-skewed distribution; almost all the prices were zero or very near zero. As a result, almost all T2 firms purchased the servo motor at this (very low) price.

At midline and endline, we no longer sought to give out servo motors at a low price, so we used the right-skewed distribution for all treatment groups (i.e. T2 as well as T1 and C).

We randomized the treatment within strata defined by product type and firm size. The types of products were (i) only shoes, (ii) only bags, or (iii) mixed, and the firm size groups were defined by the number of stitching machines in operation: (i) 2 machines, (ii) 3-5 machines, or (iii) 6 or more machines. In total, there were 9 strata.

3.6 Balance Tests

Table 1 compares the characteristics of the control and treatment arms in the baseline sample of 505 firms and reports t-tests comparing the means of each treatment group to the control group. None of the tests are significant at the

10% level, suggesting that the randomization succeeded in achieving balance. Appendix Table A.1 repeats the balance test for the set of 473 non-attriters, using information from the baseline survey. None of the t-tests are significant at the 10% level, except for that comparing the respondent's years of education between control (mean of 5.96 years) and T1 (mean of 6.65 years), which has a p-value of 0.10. This suggests that balance was preserved in the endline.

4 Econometric Strategy

Our goal is to estimate the direct effect of our T1 and T2 interventions along with the spillover effect of being "exposed" to a treated firm. Some firms may be systematically more likely to be exposed to treated firms, for instance because they are located in denser neighborhoods or are more central in communication networks. This could lead to omitted variable bias (OVB) in the coefficient estimates of exposure in a naïve regression. To remove this bias, we follow Borusyak and Hull (2023) in constructing a measure of *expected exposure to treatment*. We can think of observed exposure as one realization of a *shock assignment process* and simulate the shock assignment process 1000 times to generate counterfactual values of exposure. The average of these draws is a firm-level measure of expected exposure. Once this measure have been constructed, Borusyak and Hull (2023) suggest two related solutions to the omitted-variables bias. One is a control-function approach, which includes the expected exposure as a control variable in the regression of the outcomes on firms' treatment assignments and actual, observed exposure. The second solution is to use *recentered exposure*, the difference between the observed and expected exposure, as an instrument for the observed exposure. In either case, it is the difference between actual and expected exposure that is identifying the coefficient on exposure. In our baseline regressions, we use the control-function approach.

In our baseline specifications, we assume a simple parametric form for exposure: an indicator for whether a firm has a T2 firm within a certain walking

distance. We estimate ANCOVA regressions of the form:

$$\begin{aligned} y_{ijs} &= \beta_0 + \beta_1(T1_i) + \beta_2(T2_i) + \beta_3 Exposure^d_{T2} \\ &+\beta_4(\mathbb{E}[Exposure^d_{T2}]) + \lambda_j + \upsilon_s + y^{baseline}_{ijs} + \varepsilon_{ijs} \end{aligned} \tag{1}$$

where y_{ijs} is an outcome for a firm i at endline, in stratum j, located in sub-district (upazila) s. The indicators $T2_i$ and $T1_i$ denote whether firms are randomly allocated to T2 and T1, respectively. We include strata λ_j and subdistrict υ_s fixed effects in all our specifications. Coefficients β_1, and β_2 are the treatment effects of the intervention on T1 and T2 firms compared to control firms respectively. $Exposure^d_{T2}$ is an indicator for whether a firm is exposed to a T2 firm within a radius (in meters) of up to 1000 m ($d \in \{250, 1000\}$). For our baseline specification, we consider exposure to any T2 firm within a distance of 500m. $\mathbb{E}[Exposure^d_{T2}]$ is the average value of 1000 different simulations of the exposure term. This term controls for non-random proximity to T2 firms. To increase precision, we also include baseline values of the outcome variable, $y^{baseline}_{ijs}$. In the Appendix, we also present results following the instrumental variable approach of Borusyak and Hull (2023). For statistical inference, we present two sets of standard errors for each coefficient estimate. The first, reported in parentheses below, are Conley (1999, 2010) standard errors, which allow flexibly for spatial correlation. In square brackets, we also report standard heteroskedasticity-robust standard errors.

We are primarily interested in the coefficients β_1, β_2, and β_3. Coefficients β_1, and β_2 are the direct effects of treatments T1 and T2. Coefficient β_3 estimates the effect of exposure to at least one T2 firm (within a radius of d meters). As equation 1 is written, the spillover effect, β_3 is restricted to be the same for firms across groups (T1, T2, control). However, since T2 firms were intensively treated, it is conceivable that spillovers on them from other T2 firms were not the same as those on T1 or control firms. To isolate spillovers on T1 and control firms, we estimate an alternate version of equation 1 in which we drop T2 firms from the sample.

As mentioned above, we implemented two cross-randomizations. Firms within the T1 group were also subdivided into T1a (informational video only) and T1b

(informational video and an installed electricity meter on a clutch motor machine). This was mainly to test whether electricity meters themselves had a treatment effect. The information regarding servo motors provided provided to both sets of firms was identical. Also, in all groups, one-half of the firms participated in an incentivized belief elicitation (see subsection 3.4). Neither of the cross-randomizations is crucial to our experiment. In presenting our results, we pool T1a and T1b firms and incentivized and non-incentivized firms. (Results are very similar when we allow consider the effects separately.) The practice of pooling in this way, while common, has been called into question by Muralidharan et al. (forthcoming). As they make clear, our estimates should be interpreted as weighted averages of effects conditional on the cross-cutting treatments, rather than as estimates of unconditional average treatment effects.

5 Results

5.1 Simple Comparisons by Treatment Group

We begin by presenting simple comparisons of our main outcome variables across survey rounds and treatment groups (T1, T2, C). These comparisons should not be interpreted as causal, since they do not address the issue of interference across units, but they are useful to illustrate salient patterns in the data. Figure 6 plots servo motor usage across groups at baseline, midline, and endline. We include two measures of usage of servo motors: an indicator for whether a firm used at least one servo motor on a stitching machine and an indictor for whether a firm used more than one servo motor. The fraction of T2 firms that used at least one servo motor increased substantially between baseline and endline rounds; this is mechanical because T2 firms received one servo motor during the intervention. We see an increase in usage between baseline and endline for T1 firms, but interestingly, we also find that the fraction of control firms using at least one servo motor increased over time. Similarly, we find increases across groups for usage of more than one servo motor, albeit slightly larger changes over time for T2 and T1 compared to control firms. A natural question is whether the adoption

among control firms is due to spillovers from treated firms or background trends in adoption (or some other effect); we return to this below.

Figure 7 presents comparisons across survey rounds for beliefs about electricity usage by a servo motor. Across treatment and control groups, beliefs about servo motor electricity usage decline over time. It appears that they decline more for T2 than T1 or C. In Figure 8, we find that willingness-to-pay increases from baseline to endline across groups. Again, these patterns are illustrative and should not be interpreted as causal.

5.2 Treatment Effects and Knowledge Spillovers Due to Geographic Proximity

We now turn to our main analysis, in which we estimate treatment effects and spillover effects simultaneously. We begin in this subsection with measures of exposure based on whether any T2 firm is within a local area; we consider other measures of exposure in subsequent subsections. We consider regressions of the form of equation 1, where in some specifications we drop T2 firms from the sample to focus on spillover effects on T1 and C firms. We focus primarily on the Borusyak and Hull (2023) control-function specification; regressions using the re-centered instrumental-variables specification are very similar (and available from the authors). While we report both Conley (1999, 2010) standard errors in parentheses and heteroskedasticity-robust standard errors in square brackets, our discussion of statistical significance is based on the former.

Adoption of Servo Motors: Table 2 presents results for adoption. We consider two measures of adoption: an indicator for whether a firm adopted or received one or more servo motors (columns 1 and 3) and an indicator for whether a firm adopted two or more servo motors (columns 2 and 4); we call the latter "intensive adoption." In this table, we consider exposure within a walking distance of 500 m. In column 1, we find that firms in the T1 group were 9 percentage points more likely on average to adopt a servo motor at the endline than the control group. T2 firms were 80.9 percentage points more likely, on average, to adopt a servo motor

relative to the control group. Since this measure of adoption includes the servo motor received as part of our intervention by T2 firms, the coefficient on T2 in column 1 should be viewed as a mechanical response to the intervention; the coefficient indicates that approximately 19% of control firms adopted (controlling for exposure effects). We find a statistically significant and positive effect of exposure to a T2 firm in a 500m radius. Exposure to a T2 firm increased the average likelihood of adopting a servo motor for all firms by 15.8 percentage points.

In column 2, we consider the intensive adoption outcome. This outcome is not mechanical for T2 firms; it only takes the value 1 if firms were convinced about the effectiveness of the technology and purchased a servo motor beyond the one they received from us. We find that T2 firms were 9.1% (column 2) more likely to adopt intensively than the control group. T1 firms were 5.7% (column 2) more likely to adopt two or more servo motors relative to the control group. Exposure to a T2 firm increased the likelihood of adopting more than one servo motor for all firms across treated and control groups by 10.5%.

In columns 3 and 4, we remove T2 firms from the sample to focus on exposure effects on T1 and C firms. In column 3, we find that T1 firms were 9.9 percentage points more likely than control to adopt at least one servo motor, and the exposure to T2 firms in a 500 m radius increased the likelihood of adoption for T1 and control firms by 19.3 percentage. In column 4, when we look at intensive adoption, we find that T1 firms were 4.8 percentage points more likely to adopt more than one servo motor and that exposure to T2 firms in a 500 m radius increased the likelihood of adoption for T1 and control firms by 10.2 percentage points.

The spillover effects we estimate are robust to the distance used when defining exposure. In Figure 9, we show the coefficient on exposure at different distances ($d \in \{250, 500, 750, 1000\}$), using the specification from column 1 of Table 2 but with exposure and expected exposure defined for different distances. We find robust evidence of spillovers at various distances. There is some evidence of decay with distances greater than 500 m, but the decay is not very rapid. Overall, we interpret the results in Table 2 and Figure 9 as reasonably strong evidence of the presence of positive spillovers at a very local level.

Beliefs about servo electricity usage: In Table 3, we present results on firm owners' beliefs about electricity consumed (kWh/day) by servo motors at the endline, in levels and logs.[13] Recall that our intervention provided electricity meter readings to T2 firms that compared average electricity consumption on one servo and one clutch motor machine. The table is organized similarly to Table 2 but with the mean from each firm owner's belief distribution as the outcome. In column 1, we find that T2 firms revised their beliefs downwards by 8.2 percentage points relative to control firms. We find negative coefficients on the beliefs of T1 firms and on exposure to T2 firms (within 500 m), but they are statistically insignificant at conventional levels. In column 2, we consider the log of beliefs about the electricity usage of servo motors. We find that T2 firms revised their beliefs downward by 0.304 log points relative to control firms, but there was no statistically significant effect on beliefs for T1 firms. Being exposed to a T2 firm in a 500 m radius led to a statistically insignificant effect on beliefs for all firms. When we remove T2 firms, in column 3 we continue to find a statistically insignificant but negative coefficient on T1 firms, but a marginally significant downward revision in beliefs of 0.085 log points in column 4. The coefficient on exposure to T2 firms within 500 m remains statistically insignificant. We show the coefficient on exposure at different distances ($d \in \{250, 1000\}$) in Figure 10.

The lack of evidence of spillover effects on beliefs, despite the robust spillover effects on adoption, is notable. It appears that owners may have received positive signals about the servo motors, either directly from neighbors or indirectly, for instance through worker flows, and decided to adopt without updating their understanding of the electricity cost savings.

Willingness to pay (BDM): In Table 4, we look at willingness to pay for a servo motor in levels (BDT) and logs. The specifications are similar to those in Table 2 except for the dependent variable. In columns 1 and 2, we find that the willingness to pay for T1 firms was 267 BDT and 7.1 percentage points higher than control firms. We find that T2 firms' willingness-to-pay was 259 BDT and 4.9 percentage points higher than control firms. Notably, the increase in willingness to

[13] For details on the belief elicitation process, see section 3.4.

pay was of similar magnitude for both treatment groups. As for beliefs, however, we do not find any statistically significant effect of exposure to T2 firms nearby. In columns 3 and 4, when we exclude T2 firms from the sample, we still find no evidence of spillovers from exposure to a T2 firm. We show coefficients on exposure at different distances in Figure 11 and do not find any evidence of spillovers on willingness to pay.

Firm-level outcomes: In Table 5, we look at two measures of firm-level costs: log total costs of operations per worker (at baseline) (columns 1 and 3) and log costs of electricity per worker (at baseline) (columns 2 and 4). In column 1, we find that costs of operations per worker were lower for T2 firms by 21 log points. In column 2, the costs of electricity per worker were 15 log points lower compared to control firms. We find a statistically significant reduction in costs of operations per worker of 16 log points for T1 firms compared to control firms. In column 4, T1 firms had a lower cost of electricity per worker, but the effects are not statistically significant. Across columns, we do not find evidence of spillovers between firms. In Table 6, we look at the inverse hyperbolic sine transformation of sales in the previous month and log of number of production workers at endline. We do not find any statistically significant effects for T1, or T2 firms, nor any evidence of spillovers between firms.

Summing up, there is evidence that T2 and, in some specifications, T1 reduced firm-level costs. But these effects are not visible in sales or employment, likely in part because many factors beyond motor electricity use contribute to overall firm sales and employment. Again, we find little evidence of spillovers on firm-level performance variables. One possible explanation is that these variables are noisier than the adoption variable. This underscores the value of observing technology choices directly.

5.3 Intensity of Geographic Exposure

In the previous subsection, we defined exposure as having any T2 firm within a given distance. In this subsection, we consider the effect of the density of T2 firms within a very local area. We define four measures of exposure based on bins

of the number of T2 neighbors within a given distaince. Specifically, we define indicators based on where there are 1-2, 3-5, 6-8, or more than 8 T2 firms within 500 m. Four expected exposure measures are calculated accordingly.

The results are in Table 7. In column 1, we find statistically significant treatment effects of T1 and T2, as before. We also find positive, statistically significant coefficients on exposure to different numbers of T2 firms. The coefficients increase monotonically. The more T2 firms within a local area, the greater are the spillover effects. This pattern is also evident in column 3, where we have dropped T2 firms to focus on spillovers to T1 and control firms. Although the estimates for intensive adoption in column 2 for the full sample are neither statistically significant nor monotonic, we see the monotonic pattern for intensive adoption when we drop T2 firms in column 4.

When considering intensive adoption in columns 2 and 4, we do not does not persist for intensive adoption in column 2. But in column 3, we continue to find monotonically increasing spillovers from exposure to a larger number of T2 firms. In column 2, we estimate the effect of network density on whether the firm adopted more than one servo motor. Although we find statistically significant treatment effects on T1 and T2 firms, we do not find robust evidence for spillovers from exposure to larger numbers of T2 firms. In column 4, we exclude T2 from the estimating sample and find that spillovers increase monotonically with exposure to larger numbers of T2 firms. Taken together, we find robust evidence of larger spillovers on the adoption of at least one servo motor across firms when they are exposed to more T2 neighbors. However, the effects of network density on the adoption of more than one servo motor are relatively weaker.

5.4 Exposure Through Business Communication Networks

Another channel through which knowledge spillovers about new technologies may occur is through firms' business communication networks. To measure firms' networks, we asked firms in the baseline and midline surveys to list the other firms they would ask for advice about a new technology. In the endline survey, we firms to list other firms with whom they have communicated regarding business-

related matters. We then matched the listed firms to the directory of firms in our sample. We consider the set of contacts listed by a firm that are in our randomization sample as the firm's business communication network. Assuming that this network did not change because of the intervention, we combine the responses across the three survey rounds to construct an alternate exposure measure, i.e., whether the firm was exposed to a T2 firm in its communication network.

To understand whether this exposure measure led to spillovers in servo motor adoption, we again estimate specifications of the form of equation 1 but where exposure is an indicator for having a T2 firm within the firm's business communication network (and expected exposure is calculated using this exposure measure). In Table 8, we look at treatment effects on T1 and T2 and the spillovers from business communication networks on the two measures of adoption. The treatment effects across columns 1 through 4 on T1 and T2 firms are similar to the corresponding columns in Table 2. However, in contrast, we find no statistically significant effects on spillovers through communication networks.

The non-result for spillovers on adoption through the communication network is striking. One possible explanation is that it is important for owners to see a servo motor in action, and they are only able to do that if there is a T2 firm nearby. Another possible explanation is that owners do not readily share information about new technologies with each other, perhaps because they are competitors in product markets. We return to these possibilities below.

6 Mechanisms

In this section, consider mechanisms that may be underlying the reduced-form relationship between local exposure to another T2 firm and adoption of servo motors.

6.1 Interactions with Nearby T2 Firms

Geographical proximity may lead to various types of social interactions between firm owners. To shed light on these various kinds of interactions between firms,

we collected information at endline on the mosque, machinery supplier, and repair shop most frequently visited by the firm owner. We also asked each firm to provide a list of 5 firms with whom they had discussed servo motors. Using these measures, we generated three indicator variables of interactions with T2 firms: (i) whether the firm discussed servo motors with a T2 firm (0/1), (ii) whether the firm manager visited a mosque that was also frequented by a manager of a T2 firm (0/1), and (ii) whether the firm shared a machine supplier/repair shop/motor technician with a T2 firm (0/1). To understand whether the likelihood of such interactions is affected by proximity to a T2 firm, we use the three outcome variables and estimate equation 1 for the full sample as well as a subsample excluding the T2 treatment arm.[14]

We present the results in Table 9. In columns 1 through 3, we include all firms in the sample and present estimates from equation 1, while in columns 4 through 6, we exclude T2 firms from the sample. In columns 1 and 4, we find that firms were 16.5% and 24% more likely to discuss servo motors with a T2 firm if there was a proximate T2 firm in a 500 m radius. In column 2 and 5, we find that firms that had a T2 firm in a 500m radius, are 12.2% and 8.5% more likely to visit the same mosque as a T2 firm. Finally, in columns 3 and 6, we do not find any evidence that proximity to T2 firms mattered for whether firms share a machinery supplier, repair shop, or motor technician with a T2 firm. Overall, we find evidence for various kinds of interactions among proximate firms that are likely sources of knowledge spillovers about servo motors.

6.2 Evidence from Sharing of Meter Report Cards

As discussed in section 3.2, we provided monthly meter readings to T1b and T2 firms after the midline survey. For T1b firms, this only included the monthly readings on their clutch motor machine. For T2 firms, the report included a comparison of the monthly electricity consumption and electricity consumption per hour on their clutch and servo motor machines. Sharing and discussing these meter reports may have been another direct channel through which knowledge

[14]Note that for these outcome variables, we do not estimate ANCOVA regressions because these measures were only collected at the endline.

spillovers occurred.

In the endline survey, we also asked each owner whether other firms had shown their electricity use report cards to him or her. Using the responses to this question, we construct an indicator for whether the firm discussed or was shown an electricity meter report card by a T2 firm. We use this indicator variable to understand whether information sharing on meter reports occurred through proximate T2 firms, or through T2 firms in the business communication networks of firms. To do so, we estimate equations 1 for the full sample as well as a subsample excluding firms in the T2 treatment arm. For each of these samples, we estimate the regression using the exposure measures for having a T2 firm within a walking distance of 500m, and for having a T2 firm in the business network. The results are presented in Table 10. In columns 1 and 3, we find that firms were 2.9% and 1.9% more likely to have seen (or discussed) a meter reading report with a T2 firm if they were exposed to a T2 firm in a 500 m radius. However, in columns 2 and 4, we do not find any statistically significant effect of being exposed to a T2 firm in their business communication network on being shown/discussed the meter reading report with a T2 firm. These results also suggest that firms had face-to-face interactions with other T2 firms in their vicinity, and these discussions included showing meter report cards highlighting the electrical efficiency of servo motors. However, there was no evidence of such spillovers within business communication networks.

7 Social Benefits of the Intervention

In this section, we present an estimate of the total benefits from our intensive treatment intervention which fully subsidized the replacement of a clutch motor with a servo motor in each T2 firm. This exercise takes three types of benefits generated by the intervention into account. The first, as estimated in section 2.3, is the resulting electricity savings. These savings reflect the "private" benefit accruing to a T2 firm from switching to a servo motor.[15] The switch from a

[15]Note that these benefits may be shared with leather goods and footwear consumers through lower prices.

clutch to a servo motor also generates two types of "external" or "social" benefits which could justify a government subsidy for switching: environmental benefits from lower electricity consumption and positive adoption spillovers to other firms (which in turn generate their own private and environmental benefits).

We quantify these benefits in terms of the Marginal Value of Public Funds (MVPF), following the approach used recently by Hahn et al. (2024) to assess the benefits of over 90 environmental policy changes studied over the past 25 years.

First, we assess the environmental benefits of the intervention, focusing on the CO2 emissions abatement caused by the reduction in electricity consumption realized by switching from clutch to servo motors. As discussed in section 2.3, the meters installed by us in T2 firms reveal that on average, a clutch motor driven stitching machine consumes 0.064 kWh of electricity per hour while a servo motor driven stitching machine consumes 0.019 kWh per hour. Assuming that stitching machines are used for 160 hours per month, this implies that clutch and servo motor driven stitching machines consume, respectively, 123 kWh and 36 kWh of electricity per year. Using the estimated Operating Margin Grid Emission Factor for Bangladesh (UNFCC, 2021), which equals 528 grams of CO2 emissions per kWh, this amounts to 64,944 grams of annual CO2 emissions for one clutch motor driven stitching machine compared with 19,261 grams of CO2 emissions for one servo motor driven stitching machine. This suggests an annual reduction of CO2 emissions by around 45,683 grams (or 0.046 metric tons) by replacing one clutch motor with a servo motor.

According to the most recent EPA estimates of the social cost of carbon, 1 metric ton of CO2 emissions in 2020 would cost society USD 193 in present discounted value terms due to its contribution to global warming (EPA, 2023).[16] Therefore, the environmental value of reducing CO2 emissions by 0.046 metric tons is USD 8.74. In other words, the monthly environmental benefits from replacing one clutch motor with a servo motor are approximately USD 0.73.[17] Note

[16]The EPA presents social costs of greenhouse gases in 2020 for three near-term Ramsey discount rates: 2.5%, 2% and 1.5% (U.S.EPA, 2023). Following Hahn et al. (2024) and others in the environmental economics literature, the USD 193 estimate we use corresponds to a near-term Ramsey discount rate of 2%.

[17]Hence, taking both private and environmental benefits into account, the payback period of the servo motor used in our intervention (which has a price of USD 46) is approximately 28

that this does not include the benefits from the abatement of other GHG gases and other, more local environmental benefits such as a reduction in particulate matter pollution originating from the electricity generation sector. We were unable to find quantified estimates of these benefits for Bangladesh's electricity sector.

Given the monthly flow of monetized benefits calculated above, we estimate the Present Discounted Value (PDV) of the benefits from servo motors by applying the annual discount rate of 2 percent used by Hahn et al. (2024). [18] We also assume that new servo motors have a life of 10 years.[19] With these assumptions, the PDV of the environmental benefits of switching to a servo motor is approximately USD 99.

Next, we quantify the spillover adoptions that may arise when a firm switches to a clutch motor through simulations. In the simulation exercise, we consider a program that randomly seeds one-third of the firms in our sample. This simulation exercise resembles our intervention in the sense that approximately one-third of our sample was assigned to the T2 arm and received a servo motor from us. In each simulation, we randomly select one-third of the firms in the study sample as the seed group. Using our location data, we identify the number of firms exposed to at least one of the seeded firms (that is, within 500 meters of it). We multiply that number with the estimated impact of exposure on adoption (Table 2, column (1b)) to estimate the mean number of spillover adopters in the given simulation. We also estimate second-order spillovers (that is, impacts on firms exposed to at least one of the firms exposed to a seeded firm). We repeat this process for 1000 simulations.

months. In comparison, as estimated in section 2.3, the purely private payback period of servo motors is 51 months. Gerarden et al. (2017) make a useful distinction between the "private energy-efficiency gap" and "social energy-efficiency gap." If firms have a short enough investment horizon, it may well be that not adopting servo motor is privately optimal for firms but not socially optimal.

[18] We choose this rate for consistency with Hahn et al. (2024). US environmental studies typical used rates of 2-3 percent (e.g., Fowlie et al. (2018)). However, the Government of Bangladesh, in its cost-benefit analysis of public investments (G.o.Bangladesh, 2024), uses a considerably more conservative rate of 12 percent per annum.

[19] While we cannot verify this assumption in our setting given the recency of clutch to servo motor conversions, it is consistent with a servo motor lifespan of 20,000 to 30,000 hours, as generally claimed by specialist retailers, and our assumption that stitching machines are used for 160 hours per month in our setting.

On average across simulations, the mean total number of first- and second-order spillover adopters are, respectively, approximately 30 and 15 percent of the sample. In other words, there are 1.5 spillover adoptions per seeded firm on average, taking first- and second-order spillovers into account.

These estimates are the building blocks of our MVPF estimation. As explained in Hahn et al. (2024), the MVPF of a policy change is the ratio of the total WTP for the policy change and its net cost to the government. The policy change in our case is the fully subsidized installation of a servo motor in an existing clutch motor stitching machine. The total WTP for this policy change consists of the following components.

- The first component is the private WTP for the subsidized servo motor. This has three sub-components corresponding to three types of subsidy beneficiaries:
  - The WTP of T2 firms induced to adopt because of the intervention. This is the PDV of the electricity cost savings from the servo motor.
  - The WTP of spillover adopters. This is the PDV of the electricity cost savings from the adopted servo motors minus the one-time servo motor cost (since the motors purchased by spillover adopters are not subsidized).
  - The WTP of inframarginal T2 firms; that is, those T2 firms that would have installed servo motors regardless of the intervention. Our T2 impact estimates in Table 2 imply that 20% of the T2 firms would have installed the motors anyway. The WTP of these inframarginal T2 firms is the subsidy amount.
- The second component is the environmental benefit associated with each beneficiary type. Its value per servo motor adoption is the same for the T2 firms induced to adopt by the intervention and the spillover adopters. Its value is zero for inframarginal T2 firms.

We systematically summarize these components and the associated WTP values in Table 11. Summing them up and dividing them by the net cost of the policy

change (the price of the servo motor, ignoring administrative costs), we arrive at an MVPF 7.7. For context, this number is in the upper range of the 90 plus MVPF estimates calculated in the Hahn et al. (2024) meta-analysis of environmental policy changes studied over the past 25 years; specifically, Hahn et al. (2024) consider MVPFs above 5 to be high in their sample of studies, which are overwhelmingly from the US. However, we should note that the MVPFs estimated in their smaller subsample of studies from developing countries tend to be higher, with a third of them ranging between 5 and 15, and two of them even exceeding 100. Notably, the intervention to promote energy efficient cookstove adoption studied in Berkouwer and Dean (2022) is estimated to have an MVPF above 300.

As shown in Table 11, had we ignored spillover benefits, the MVPF from our intervention would be around 3. Put otherwise, more than half of our MVPF of 7.7 is accounted for by spillovers.

We note two limitations of our MVPF estimate. First, it does not include the benefits from the abatement of GHG gases other than CO2; nor does it include more local environmental benefits such as a reduction in particulate matter pollution originating from the electricity generation sector. We were unable to find quantified estimates of these benefits for Bangladesh's electricity sector. Second, our estimate does not account for potential rebound effects on electricity usage.

Finally, we note that in our setting, the total gains from large-scale adoption of servo motors are substantial. Using data from the World Bank Firm Level Adoption of Technology survey, we estimate that approximately 76,000 stitching machines with clutch motors were being used in Bangladesh's RMG and leather goods sectors in 2019.[20] The total PDV (private plus environmental, net of servo motor cost) from switching all of these clutch motors to servo motors is of the order of USD 9.8 million.

[20]We partnered with the 2019 World Bank Firm Level Adoption of Technology survey (Gu et al., 2021) to gather background information for our study. The survey collected data on the number of stitching machines and their motor types among firms in the RMG and leather goods industries. The sample frame for the survey was based on the 2013 Bangladesh Business Directory and firm lists shared by industry associations.

8 Conclusion

This paper has presented what we believe is the first experimental study of knowledge spillovers about a naturally occurring production technology among manufacturing firms in an urban setting. We treated firms with an information-only treatment (T1) or an information-and-installation treatment (T2). Using the Borusyak and Hull (2023) re-centering approach to estimate direct and indirect effects of our interventions simultaneously, we find direct effects of both treatments and, perhaps more importantly, robust, positive, very local spillover effects from T2 firms. Having at least one T2 firm within 500 meters has a greater positive effect on adoption than receiving a 20-minute informational video about the technology. Geographic distance is revealed to be very important. We find little evidence of spillovers within firms' communication networks.

These findings contribute to a deepening empirical understanding of the microfoundations for agglomeration economies. The idea that knowledge spillovers are an important reason why firms cluster together geographically has had influential adherents at least since Marshall (1890), but there have been few rigorous micro-empirical studies. In Dhaka, rents in the dense Bangshal neighborhood (Old Dhaka) are significantly higher than in other industrial areas within the city (Hazaribagh, Kamrangirchar). It is natural to ask why firms would be willing to pay these higher rents. Our study provides a clear answer: they are more likely to be exposed to knowledge spillovers. There may be other reasons for local exposure effects, including worker flows and reduced client search costs. Teasing apart the relative importance of knowledge spillovers and other sources of agglomeration economies is a topic for future work. What seems clear, though, is that knowledge flows are occurring at a very local level in the leather-goods industry in Dhaka.

Our findings have potentially important implications for debates in environmental economics about how to mitigate climate change. A marginal value of public funds (MVPF) calculation which takes into account learning spillovers as well as emissions reductions by treated firms yields a value of 7.7, which compares well to the broad set of environmental policies that Hahn et al. (2024) con-

sider. Notably, this value is more than double the MVPF that we would obtain if we ignored the learning spillovers. This result underscores the importance of considering learning spillovers when designing policies to encourage green technology adoption. It also suggests that subsidies for servo motors would be a promising policy intervention.

One question that our study does not answer is what would be the optimal way to inject information about new technologies into existing networks. In the interests of simplicity, we assigned equal probabilities to T1, T2 and Control, without attention to network structure. Work by Banerjee et al. (2013) and others suggests that adoption and overall welfare could be increased by more judicious choices of the firms to subsidize. This is another topic for future work.

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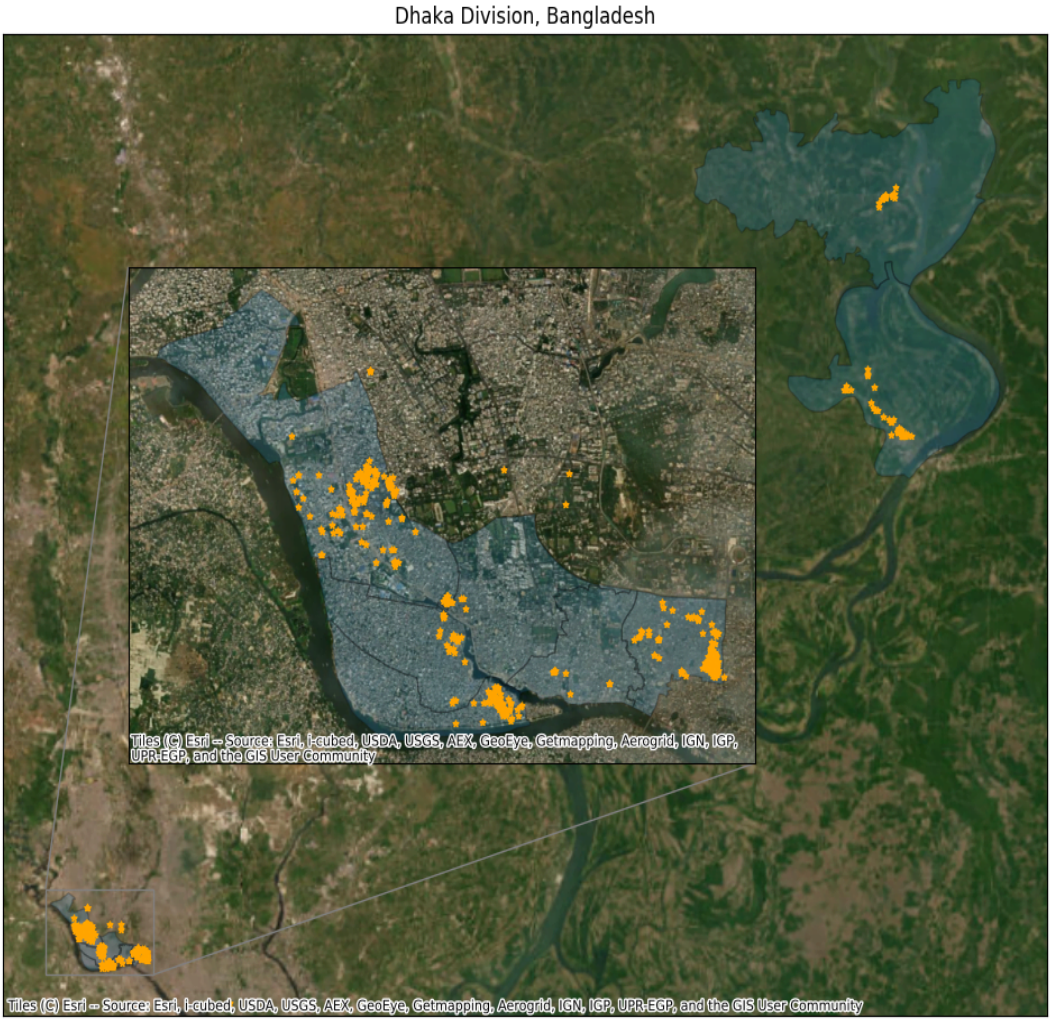
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Figure 1: Dhaka, Bangladesh



Note: The map shows the Dhaka division administrative unit covering the areas of Old Dhaka (in the bottom left) and Bhairab (in the top right). The firms that constitute the final study sample are marked in orange. The inset in the middle shows a zoomed-in view of Old Dhaka and the main clusters within.

Figure 2: Bangshal, Dhaka

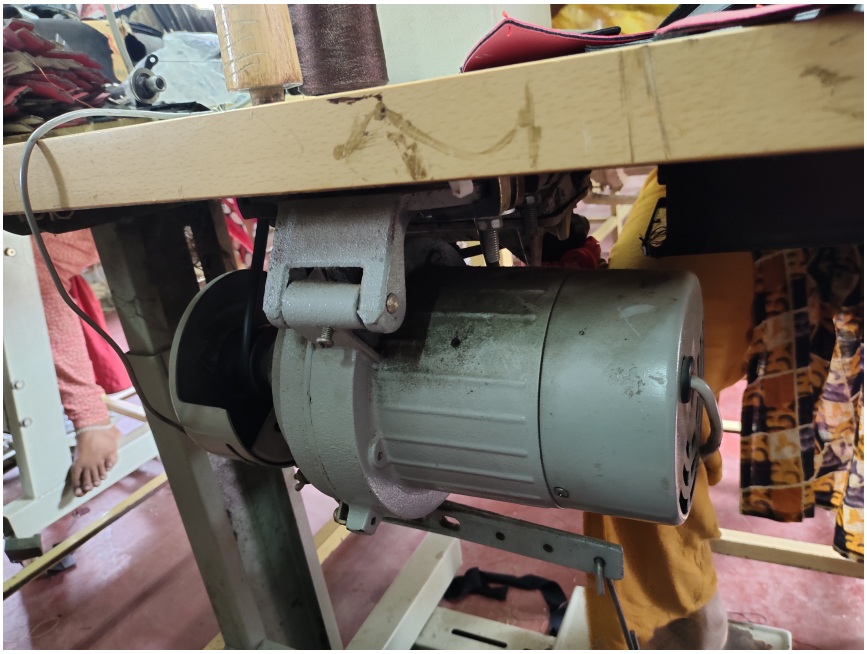


Notes: The figure at the top shows the Bangshal upazila administrative unit in old Dhaka. The cluster of firms selected for the study are marked in orange. The figure at the bottom zooms in on the location of the main cluster within Bangshal, with the buildings and main roads marked out.

Figure 3: Servo and Clutch Motors

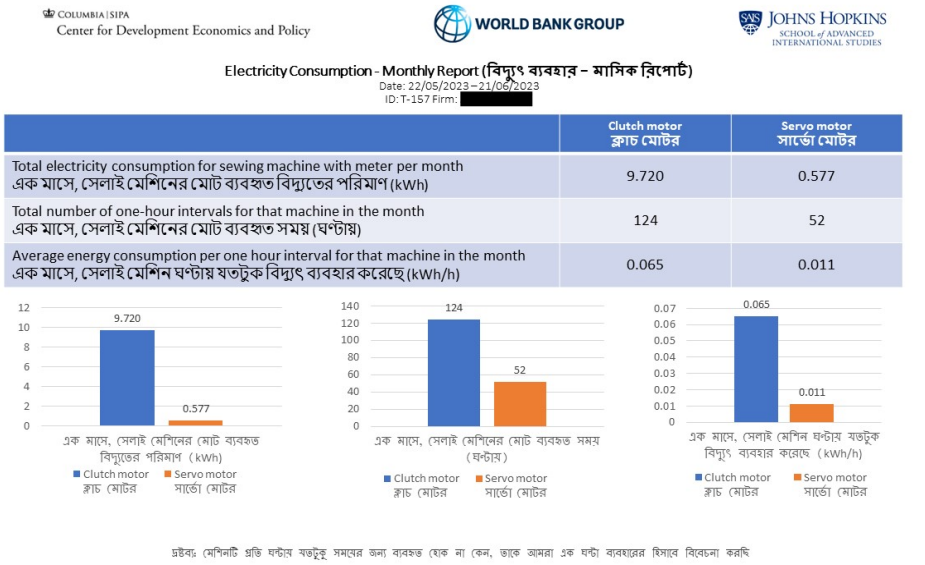


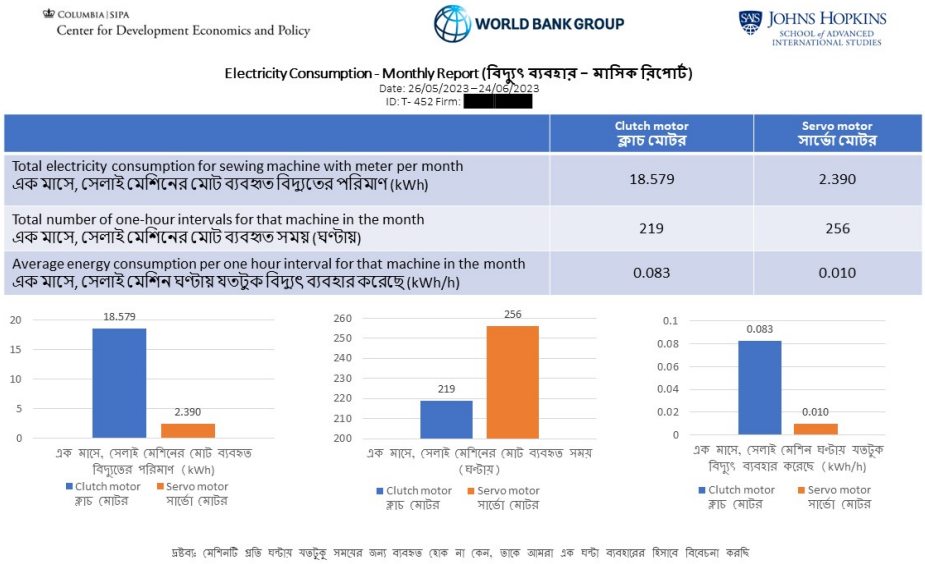
Servo motor



Clutch motor

Figure 4: Examples of meter reading reports presented to T2 firms

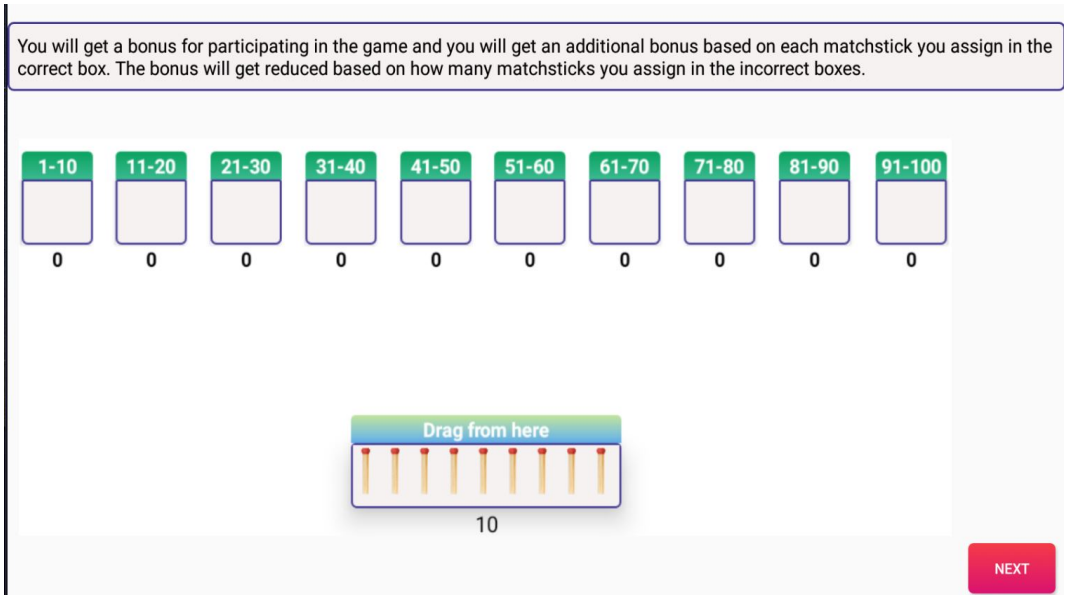




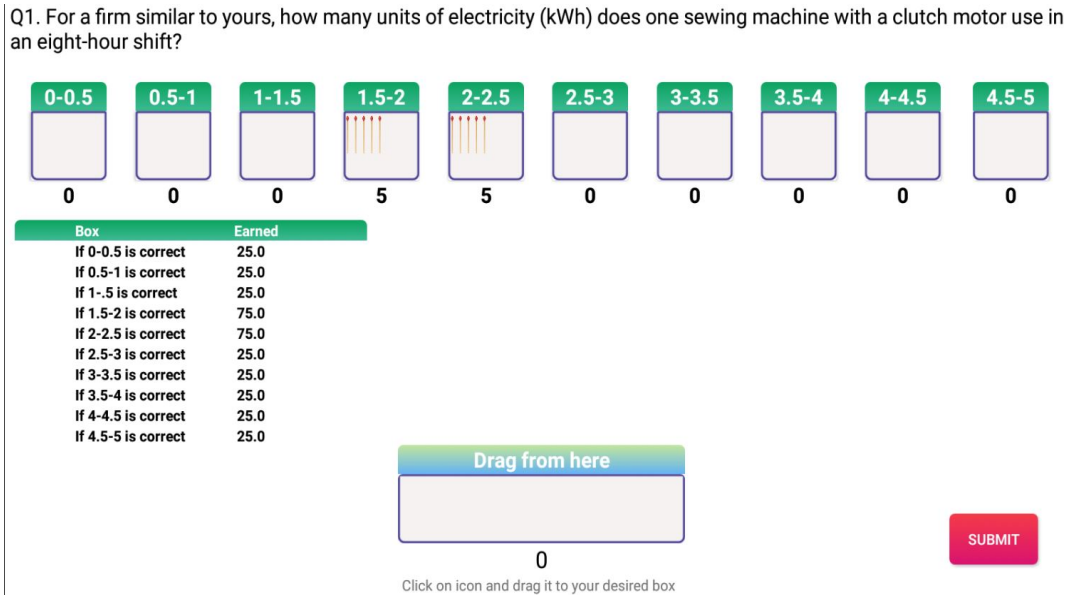
Note: These are two examples of monthly meter reading reports presented to T2 firms. The report presents the total electricity consumption, the total number of one-hour intervals in which the machine was running, and the implied mean electricity consumption per hour in the previous month for the two machines in the firm in which we installed meters. One of them was a clutch motor machine, and the other was a machine in which we replaced the clutch motor with a servo motor.

Figure 5: Screenshots from belief-elicitation tablet app

A. Introducing "drag and drop" matchstick allocation and reward scheme

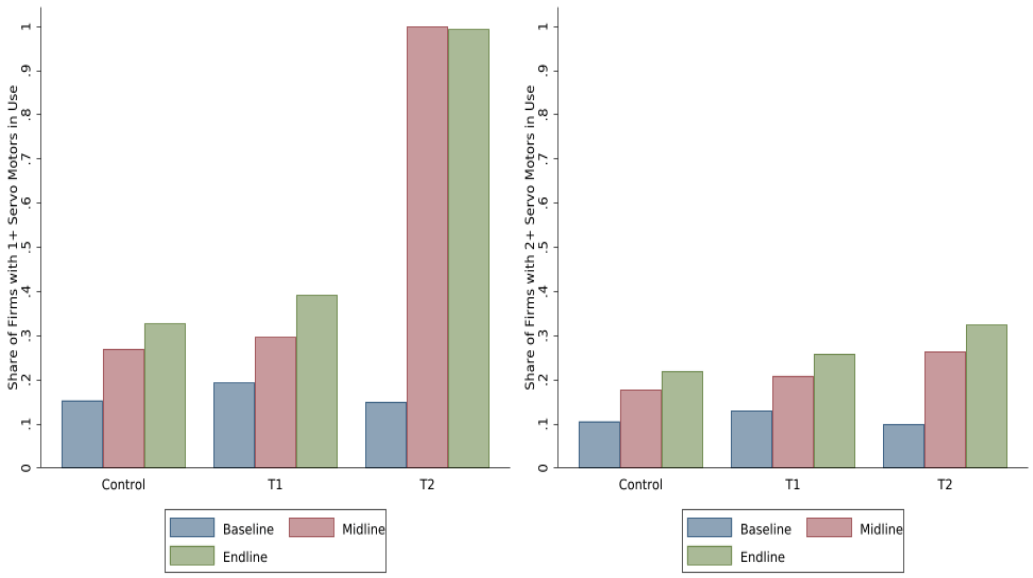


B. An example of a belief-elicitation question screen



Note: This figure presents screenshots from our tailor-made incentivized belief-elicitation app for tablets. Panel A introduces the respondent to the drag and drop matchstick allocation feature and explains how they will be rewarded. The respondent then plays two practice rounds (not shown here) before moving to the actual BE questions. Panel B presents the first BE question. In this screenshot, the respondent has made an allocation but not locked it in. The table below the bins presents the reward from this allocation based on different assumptions about the correct bin. This table is updated in real time as the allocation changes.

Figure 6: Simple Comparisons: Usage of servo motor

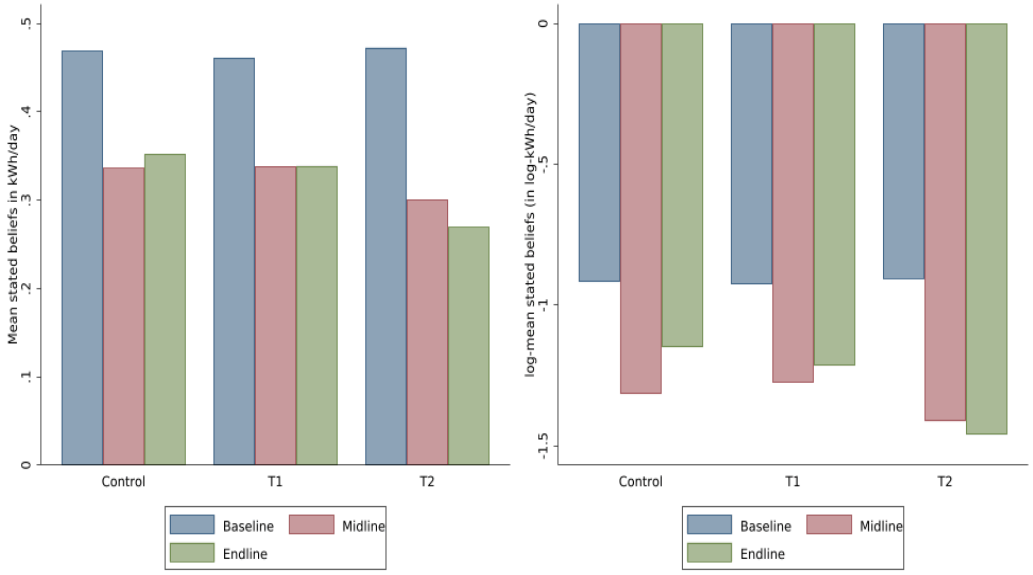


A. Usage of 1+ Servomotors (0/1)

B. Usage of 2+ Servomotors (0/1)

Notes: The usage of servo motors reflects whether the firm reported using at least one (or at least two) machines with a servo motor at the time of the survey round. The left panel shows the proportion of firms that reported using at least one servo motor, while the right panel shows the proportion of firms that reported using at least two servo motors.

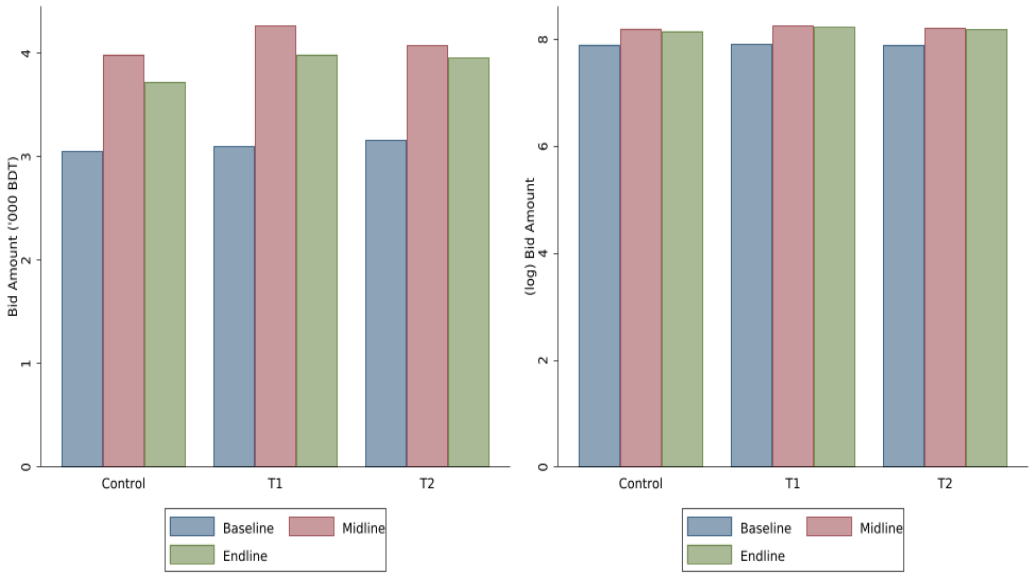
Figure 7: Simple Comparison: Beliefs



A. Beliefs about servo electricity usage B. log beliefs about servo electricity usage

Notes: Beliefs are group averages of means of distributions reported by individual managers/owners; depicted here in levels and logs.

Figure 8: Simple Comparison: Willingness-to-Pay

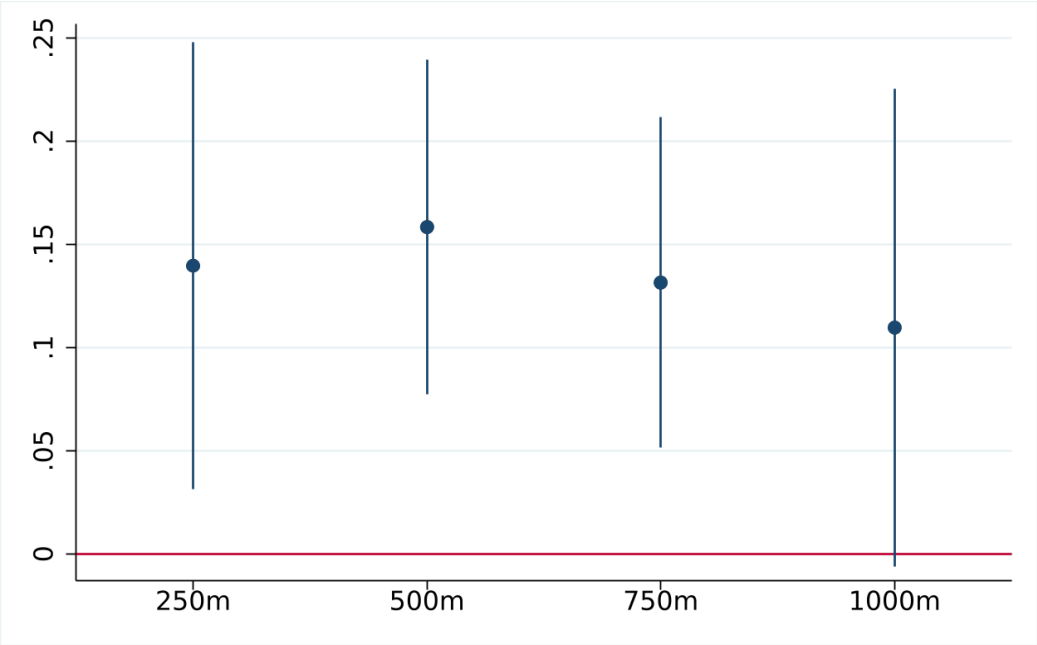


A. BDM Bid (000s BDT)

B. log BDM Bid

Notes: In the experiment we elicit the willingness-to-pay for a servo motor using the Becker, DeGroot and Marschak (1964, BDM) procedure. The left panel depicts the final bid placed by the firm in levels, and the right panel in logs.

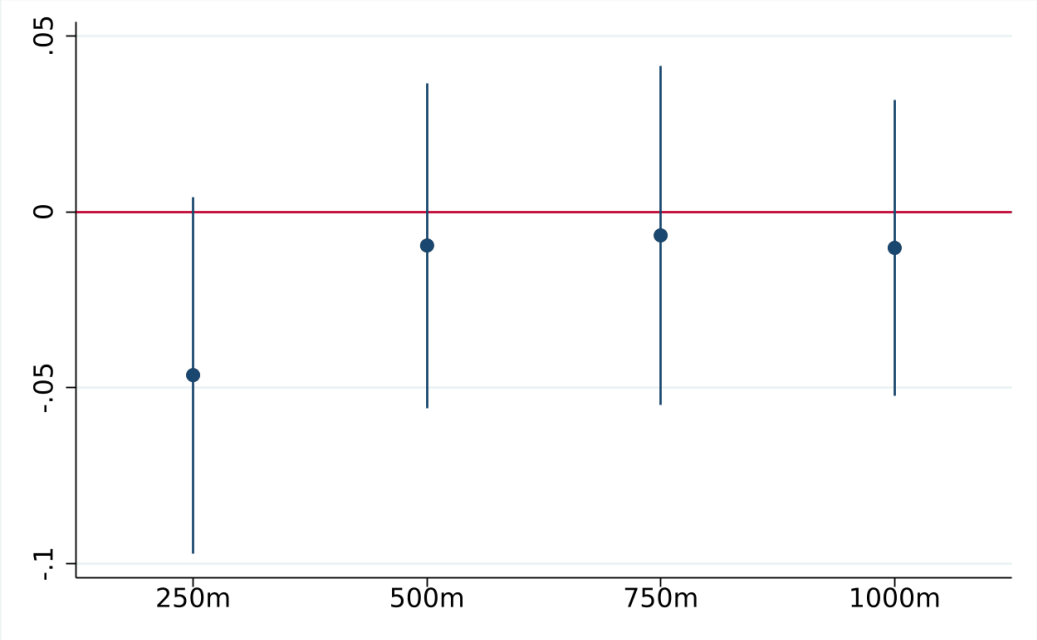
Figure 9: Spillovers in Servo Adoption, by Distance



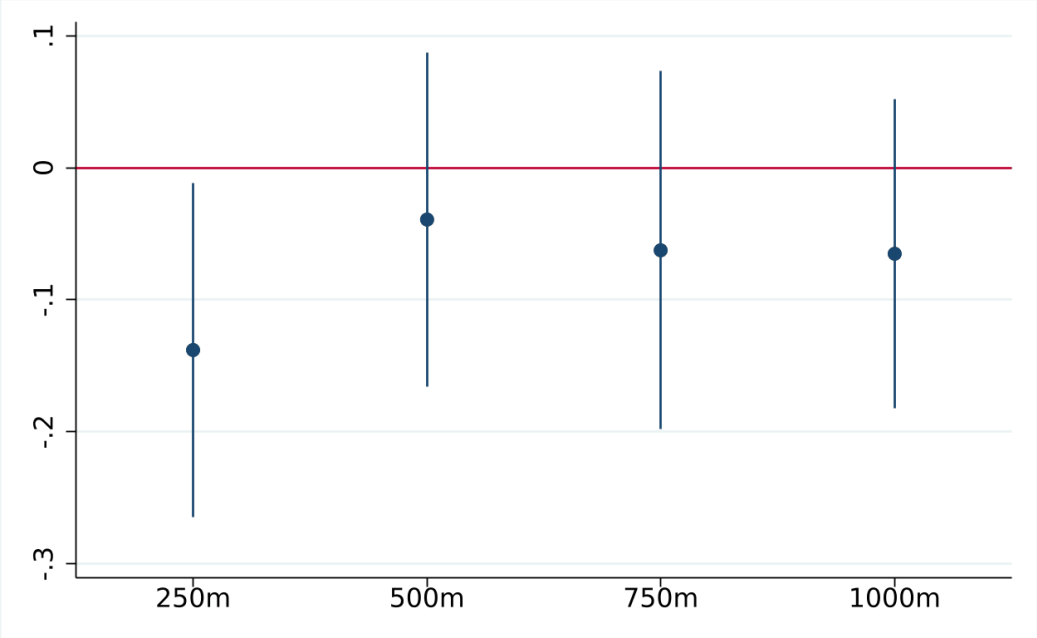
Note: Figure plots the estimates and 90% confidence intervals on the exposure term from equation 1 in text, at various distances. Dependent variable is 0/1 indicator for having purchased 1+ servo motors between baseline and endline. The standard errors use the spatial correction from Conley (1999).

Figure 10: Spillovers in Beliefs, by Distance

A. Beliefs about servo elec usage (kWh/day)



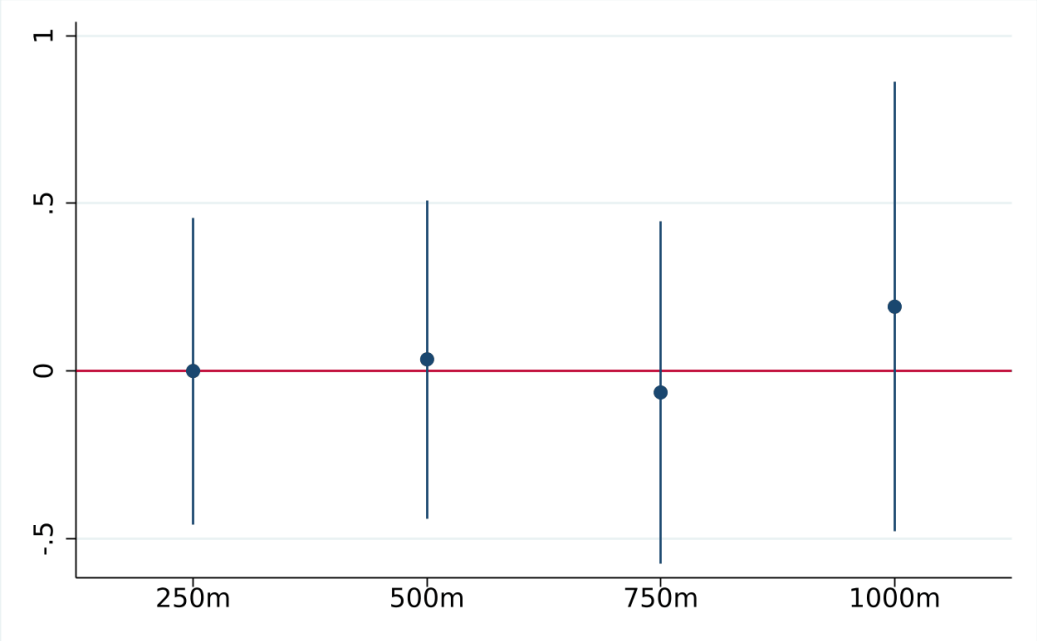
B. log beliefs about servo elec usage (kWh/day)



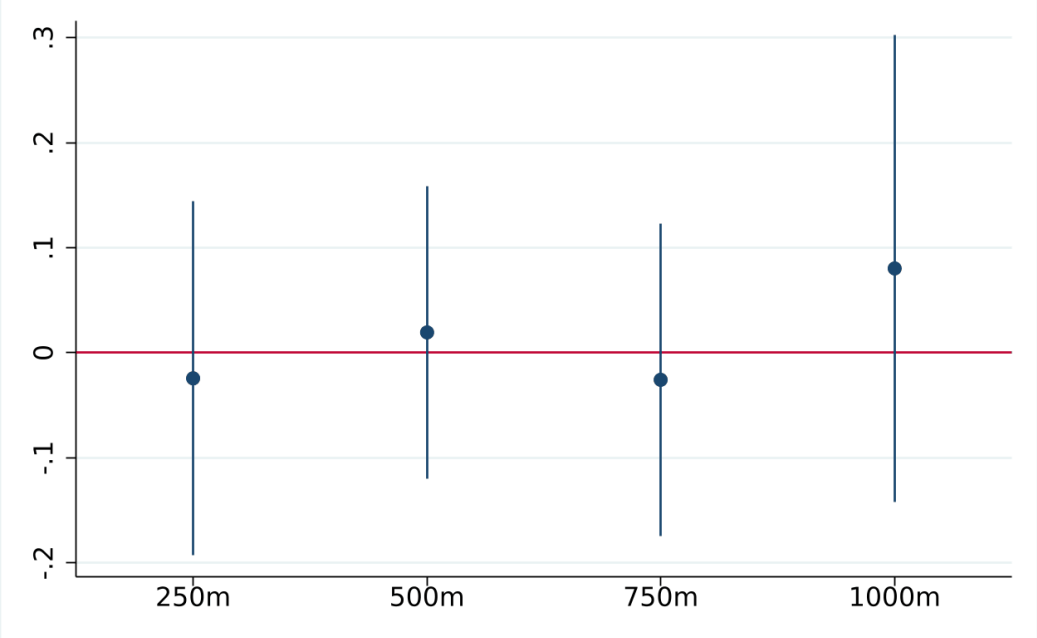
Note: Figure plots the estimates and 90% confidence intervals on the exposure term from 1 in text, at various distances. Outcome is the mean of the distribution of beliefs about electricity use of a servo motor, in levels and logs. The standard errors use the spatial correction from Conley (1999).

Figure 11: Spillovers in BDM Bid, by Distance

A. BDM bid (000s BDT)



B. log BDM bid



Note: Figure plots the estimates and 90% confidence intervals on the exposure term from equation 1 in text, at various distances. Outcome is a firm's willingness-to-pay for a servo motor in levels (000s of BDT) and logs, elicited using the Becker, DeGroot and Marschak (1964, BDM) procedure. The standard errors use the spatial correction from Conley (1999).

Table 1: Balance Table for Sample at Baseline

	N.Obs	Control	T1	T2	P-value, Control=T1	P-value, Control=T2
	(1)	(2)	(3)	(4)	(5)	(6)
Num. of Machines						
Num. machines (total)	505	5.93	6.12	6.62	(0.65)	(0.59)
Num. machines (non-motorized)	505	0.25	0.16	0.16	(0.18)	(0.16)
Num. machines (w/ ext. motor)	505	0.18	0.19	0.24	(0.86)	(0.51)
Num. machines (w/ clutch motor)	505	4.99	4.81	5.39	(0.72)	(0.83)
Num. machines (w/ servo motor)	505	0.68	0.83	0.80	(0.56)	(0.92)
Beliefs						
Beliefs, elec usage (kwh/day) for clutch motor	505	0.66	0.67	0.70	(0.79)	(0.22)
Beliefs, elec usage (kwh/day) for servo motor	505	0.47	0.46	0.47	(0.79)	(0.79)
BDM bid ('000 BDT)	505	3.05	3.10	3.16	(0.73)	(0.60)
Beliefs, price of electricity (BDT/kwh)	505	11.17	10.94	10.96	(0.24)	(0.31)
Firm Characteristics						
Production costs, last month ('000,000 BDT)	505	0.47	0.39	0.50	(0.36)	(0.95)
Profits, last month ('000 BDT)	505	30.95	26.15	37.63	(0.66)	(0.58)
Sales, last month ('000,000 BDT)	505	0.52	0.41	0.54	(0.25)	(0.93)
Electricity costs, last month ('000 BDT)	505	6.27	4.67	5.05	(0.34)	(0.33)
Firm has Servo at Baseline (0/1)	505	0.15	0.19	0.15	(0.25)	(0.63)
Employees						
Num. employees on payroll	505	10.65	10.39	12.17	(0.88)	(0.52)
Num. permanent, full-time workers	505	9.66	9.44	10.88	(0.92)	(0.65)
Num. managers, skilled professionals	505	1.38	1.48	1.57	(0.62)	(0.39)
Num. production-line workers (total)	505	9.97	9.62	11.41	(0.86)	(0.53)
Respondent Characteristics						
Respondent is male (0/1)	505	0.96	0.98	0.96	(0.18)	(0.91)
Respondent's years of education	505	6.09	6.58	6.52	(0.24)	(0.46)
Respondent's age	505	35.88	36.23	35.34	(0.77)	(0.47)
Respondent's experience	505	15.47	15.68	14.94	(0.83)	(0.40)
Attrited at Endline	505	0.02	0.03	0.04	(0.57)	(0.36)

Table 2: Treatment & Local Spillover Effects on Adoption at Endline

	Including T2		Excluding T2	
	Purchased or Received any motor (0/1)	Purchased or Received (2+) (0/1)	Purchased or Received any motor (0/1)	Purchased or Received (2+) (0/1)
	(1)	(2)	(3)	(4)
T1	0.090	0.057	0.099	0.048
	(0.035)**	(0.018)***	(0.033)***	(0.018)***
	[0.041]**	[0.034]*	[0.042]**	[0.034]
T2	0.809	0.091		
	(0.079)***	(0.025)***		
	[0.032]***	[0.039]**		
Exposure (500m)	0.158	0.105	0.193	0.102
	(0.049)***	(0.049)**	(0.071)***	(0.057)*
	[0.062]**	[0.062]*	[0.078]**	[0.066]
Exp. Exposure (500m)	-0.010	0.029	0.001	0.016
	(0.088)	(0.093)	(0.118)	(0.093)
	[0.098]	[0.090]	[0.133]	[0.102]
Observations	473	473	325	325
Baseline mean	0.000	0.000	0.000	0.000
P-value, T1=T2	0.000	0.366		
Upazila FE	Y	Y	Y	Y
Strata FE	Y	Y	Y	Y

Notes: Estimates are of equation 1 in text, but without dependent variable at baseline. Exposure (500m) is 0/1 indicator for having 1 or more T2 firm within a walking distance of 500m. Exp. Exposure (500m) is mean of Exposure from 1,000 counterfactual treatment assignment draws. Dependent variables are 0/1 indicators for having purchased or received (from us) 1+ or 2+ servo motors between baseline and endline. The standard errors in parentheses use the spatial correction from Conley (1999). The standard errors in square brackets are heteroskedasticity-robust (without the correction for spatial correlation). *p <0.10; **p <0.05; ***p <0.01.

Table 3: Treatment & Local Spillover Effects on Beliefs at Endline, with ANCOVA/ baseline controls

	Including T2		Excluding T2	
	Beliefs about servo elec. usage (kWh/day) (1)	(log) Beliefs about servo elec. usage (kWh/day) (2)	Beliefs about servo elec. usage (kWh/day) (3)	(log) Beliefs about servo elec. usage (kWh/day) (4)
T1	-0.020	-0.083	-0.021	-0.085
	(0.013)	(0.038)**	(0.014)	(0.044)*
	[0.018]	[0.052]	[0.018]	[0.052]
T2	-0.082	-0.304		
	(0.011)***	(0.030)***		
	[0.018]***	[0.057]***		
Exposure (500m)	-0.013	-0.056	-0.026	-0.099
	(0.029)	(0.078)	(0.032)	(0.081)
	[0.030]	[0.087]	[0.035]	[0.101]
Exp. Exposure (500m)	-0.073	-0.255	-0.091	-0.286
	(0.042)*	(0.109)**	(0.048)*	(0.120)**
	[0.050]	[0.143]*	[0.060]	[0.165]*
Dep var at baseline	0.051	0.082	0.057	0.112
	(0.041)	(0.034)**	(0.049)	(0.046)**
	[0.031]	[0.037]**	[0.039]	[0.043]***
Observations	473	473	325	325
Baseline mean	0.466	-0.921	0.465	-0.920
P-value, T1=T2	0.001	0.000		
Upazila FE	Y	Y	Y	Y
Strata FE	Y	Y	Y	Y

Notes: Estimates are of equation 1 in text. Exposure (500m) is 0/1 indicator for having 1 or more T2 firm within a walking distance of 500m. Exp. Exposure (500m) is mean of Exposure from 1,000 counterfactual treatment assignment draws. Dependent variable is the mean of the distribution of beliefs about electricity use of a servo motor, in levels or logs. The standard errors in parentheses use the spatial correction from Conley (1999). The standard errors in square brackets are heteroskedasticity-robust (without the correction for spatial correlation). *p <0.10; **p <0.05; ***p <0.01.

Table 4: Treatment & Local Spillover Effects on BDM Bid at Endline, with ANCOVA/ baseline controls

	Including T2		Excluding T2	
	BDM bid ('000 BDT) (1)	(log) BDM bid (2)	BDM bid ('000 BDT) (3)	(log) BDM bid (4)
T1	0.267	0.071	0.260	0.069
	(0.087)***	(0.032)**	(0.091)***	(0.033)**
	[0.143]*	[0.043]*	[0.142]*	[0.043]
T2	0.259	0.049		
	(0.094)***	(0.027)*		
	[0.162]	[0.047]		
Exposure (500m)	0.084	0.037	0.035	0.010
	(0.232)	(0.066)	(0.272)	(0.076)
	[0.282]	[0.079]	[0.297]	[0.082]
Exp. Exposure (500m)	-0.102	-0.027	0.009	0.002
	(0.418)	(0.111)	(0.362)	(0.100)
	[0.450]	[0.127]	[0.475]	[0.128]
Dep var at baseline	0.199	0.174	0.133	0.117
	(0.050)***	(0.054)***	(0.020)***	(0.031)***
	[0.046]***	[0.035]***	[0.050]***	[0.039]***
Observations	473	473	325	325
Baseline mean	3.104	7.905	3.071	7.908
P-value, T1=T2	0.962	0.630		
Upazila FE	Y	Y	Y	Y
Strata FE	Y	Y	Y	Y

Notes: Estimates are of equation 1 in text. Exposure (500m) is 0/1 indicator for having 1 or more T2 firm within a walking distance of 500m. Exp. Exposure (500m) is mean of Exposure from 1,000 counterfactual treatment assignment draws. Dependent variable is a firm's willingness-to-pay for a servo motor in levels (000s of BDT) and logs, elicited using the Becker, DeGroot and Marschak (1964, BDM) procedure. The standard errors in parentheses use the spatial correction from Conley (1999). The standard errors in square brackets are heteroskedasticity-robust (without the correction for spatial correlation). *p <0.10; **p <0.05; ***p <0.01. *p <0.10; **p <0.05; ***p <0.01.

Table 5: Treatment & Local Spillover Effects on Cost of Operations and Electricity per Baseline Worker at Endline, with ANCOVA/Baseline Controls

	Including T2		Excluding T2	
	(log) Cost of operations per worker at baseline (1)	(log) Cost of electricity per worker at baseline (2)	(log) Cost of operations per worker at baseline (3)	(log) Cost of electricity per worker at baseline (4)
T1	-0.165	-0.043	-0.162	-0.052
	(0.049)***	(0.042)	(0.045)***	(0.037)
	[0.106]	[0.093]	[0.107]	[0.093]
T2	-0.211	-0.148		
	(0.071)***	(0.079)*		
	[0.106]**	[0.095]		
Exposure (500m)	0.121	0.039	-0.012	0.072
	(0.190)	(0.090)	(0.207)	(0.119)
	[0.177]	[0.140]	[0.200]	[0.159]
Exp. Exposure (500m)	-0.512	-0.466	-0.353	-0.446
	(0.303)*	(0.216)**	(0.330)	(0.271)*
	[0.292]*	[0.238]*	[0.335]	[0.279]
Dep var at baseline	0.454	0.664	0.516	0.638
	(0.050)***	(0.062)***	(0.072)***	(0.073)***
	[0.066]***	[0.066]***	[0.077]***	[0.084]***
Observations	473	473	325	325
Baseline mean	10.458	5.959	10.477	5.984
P-value, T1=T2	0.650	0.206		
Upazila FE	Y	Y	Y	Y
Strata FE	Y	Y	Y	Y

Notes: Estimates are of equation 1 in text. Exposure (500m) is 0/1 indicator for having 1 or more T2 firm within a walking distance of 500m. Exp. Exposure (500m) is mean of Exposure from 1,000 counterfactual treatment assignment draws. The dependent variable in columns 1 and 3 is log cost of operations per worker; in columns 2 and 4 it is log cost of electricity per worker. In constructing dependent variable, we use employment at baseline. The standard errors in parentheses use the spatial correction from Conley (1999). The standard errors in square brackets are heteroskedasticity-robust (without the correction for spatial correlation). *p <0.10; **p <0.05; ***p <0.01. *p <0.10; **p <0.05; ***p <0.01.

Table 6: Treatment & Local Spillover Effects on Firm Outcomes - Sales and Employment at Endline, with ANCOVA/Baseline controls

	Including T2		Excluding T2	
	(ihs) Sales, previous month	(log) Num. employees on payroll (total)	(ihs) Sales, previous month	(log) Num. employees on payroll (total)
	(1)	(2)	(3)	(4)
T1	-0.063	-0.023	-0.056	-0.029
	(0.096)	(0.060)	(0.063)	(0.056)
	[0.170]	[0.064]	[0.169]	[0.065]
T2	-0.255	0.024		
	(0.236)	(0.043)		
	[0.214]	[0.068]		
Exposure (500m)	0.043	-0.003	-0.127	0.027
	(0.207)	(0.140)	(0.239)	(0.153)
	[0.212]	[0.131]	[0.234]	[0.136]
Exp. Exposure (500m)	-0.601	-0.239	-0.350	-0.383
	(0.333)*	(0.194)	(0.426)	(0.220)*
	[0.334]*	[0.201]	[0.376]	[0.223]*
Dep var at baseline	0.507	0.675	0.518	0.630
	(0.058)***	(0.070)***	(0.078)***	(0.083)***
	[0.068]***	[0.047]***	[0.080]***	[0.057]***
Observations	473	473	325	325
Baseline mean	12.937	1.912	12.924	1.882
P-value, T1=T2	0.305	0.491		
Upazila FE	Y	Y	Y	Y
Strata FE	Y	Y	Y	Y

Notes: Estimates are of equation 1 in text. Exposure(500m) is 0/1 indicator for having 1 or more T2 firm within a walking distance of 500m. We have included ANCOVA / baseline controls for this table. The dependent variable in column 1 and 3 is the reported sales for the firm in the month prior to endline; the values are IHS-transformed as some firms report zero sales; in columns 2 and 4 it is the log of the number of employees on a firm's payroll, which includes paid workers both permanent and otherwise, as well as unpaid workers. The standard errors in parentheses use the spatial correction from Conley (1999). The standard errors in square brackets are heteroskedasticity-robust (without the correction for spatial correlation). *p <0.10; **p <0.05; ***p <0.01.

Table 7: Treatment & Local Spillover Effects of Increasing Intensity of Geographic Exposure on Adoption at Endline

	Including T2		Excluding T2	
	Purchased or Received any motor (0/1)	Purchased or Received (2+) (0/1)	Purchased or Received any motor (0/1)	Purchased or Received (2+) (0/1)
	(1)	(2)	(3)	(4)
T1	0.092	0.062	0.102	0.050
	(0.032)***	(0.017)***	(0.031)***	(0.018)***
	[0.041]**	[0.034]*	[0.041]**	[0.034]
T2	0.811	0.088		
	(0.076)***	(0.024)***		
	[0.032]***	[0.038]**		
Exposure(500m), 1-2 ngh. (0/1)	0.152	0.102	0.158	0.080
	(0.059)**	(0.052)*	(0.085)*	(0.057)
	[0.066]**	[0.065]	[0.088]*	[0.071]
Exposure(500m), 3-5 ngh. (0/1)	0.186	-0.038	0.246	0.191
	(0.100)*	(0.107)	(0.125)**	(0.092)**
	[0.109]*	[0.122]	[0.145]*	[0.121]
Exposure(500m), 6-8 ngh. (0/1)	0.295	0.038	0.416	0.271
	(0.116)**	(0.135)	(0.174)**	(0.102)***
	[0.173]*	[0.147]	[0.251]*	[0.153]*
Exposure(500m), 8+ ngh. (0/1)	0.576	0.433	0.824	0.584
	(0.104)***	(0.271)	(0.167)***	(0.087)***
	[0.239]**	[0.264]	[0.349]**	[0.274]**
Exp. Exposure(500m), 1-2 ngh. (0/1)	-0.020	-0.079	-0.008	0.053
	(0.082)	(0.129)	(0.120)	(0.107)
	[0.120]	[0.123]	[0.161]	[0.121]
Exp. Exposure(500m), 3-5 ngh. (0/1)	-0.068	0.169	-0.142	-0.103
	(0.103)	(0.210)	(0.144)	(0.145)
	[0.136]	[0.155]	[0.198]	[0.154]
Exp. Exposure(500m), 6-8 ngh. (0/1)	0.083	0.200	0.107	-0.020
	(0.113)	(0.145)	(0.176)	(0.164)
	[0.239]	[0.206]	[0.313]	[0.211]
Exp. Exposure(500m), 8+ ngh. (0/1)	-0.450	-0.318	-0.639	-0.451
	(0.118)***	(0.281)	(0.170)***	(0.091)***
	[0.255]*	[0.267]	[0.361]*	[0.268]*
Observations	473	473	325	325
Baseline mean	0.000	0.000	0.000	0.000
P-value, T1=T2	0.000	0.489		
Upazila FE	Y	Y	Y	Y
Strata FE	Y	Y	Y	Y

The estimates in this table are calculated using the Borusyak-Hull specification. Exposure, a-b ngh. (500m) is a 0/1 indicator for whether the firm has between a and b (included) T2 firm(s) within a walking distance of 500m. Dependent variables are 0/1 indicators for having purchased or received (from us) 1+ or 2+ servo motors between baseline and endline. The standard errors in parentheses use the spatial correction from Conley (1999). The standard errors in square brackets are heteroskedasticity-robust (without the correction for spatial correlation). *p <0.10; **p <0.05; ***p <0.01.

Table 8: Treatment Effects & Spillover Effects from Communication Network on Adoption at Endline

	Including T2		Excluding T2	
	Purchased or Received any motor (0/1)	Purchased or Received (2+) (0/1)	Purchased or Received any motor (0/1)	Purchased or Received (2+) (0/1)
	(1)	(2)	(3)	(4)
T1	0.091	0.060	0.100	0.051
	(0.037)**	(0.020)***	(0.036)***	(0.019)***
	[0.042]**	[0.034]*	[0.042]**	[0.034]
T2	0.810	0.096		
	(0.081)***	(0.028)***		
	[0.032]***	[0.039]**		
Exposure, network	-0.039	0.019	-0.029	-0.013
	(0.030)	(0.042)	(0.045)	(0.053)
	[0.040]	[0.038]	[0.057]	[0.044]
Exp. Exposure, network	0.080	-0.038	0.070	-0.040
	(0.056)	(0.056)	(0.081)	(0.068)
	[0.071]	[0.067]	[0.100]	[0.076]
Observations	473	473	325	325
Baseline mean	0.000	0.000	0.000	0.000
P-value, T1=T2	0.000	0.344		
Upazila FE	Y	Y	Y	Y
Strata FE	Y	Y	Y	Y

The estimates in this table are calculated using the Borusyak-Hull specification. Exposure, network is 0/1 indicator for whether the firm reported talking business with 1 or more T2 firm(s). Dependent variables are 0/1 indicators for having purchased or received (from us) 1+ or 2+ servo motors between baseline and endline. The standard errors in parentheses use the spatial correction from Conley (1999). The standard errors in square brackets are heteroskedasticity-robust (without the correction for spatial correlation). *p <0.10; **p <0.05; ***p <0.01.

Table 9: Interactions (discussions about servomotors, common third places) with Proximate T2 Firms

	Including T2			Excluding T2		
	Discussed servomotors with a T2 firm (0/1)	Same mosque as a T2 firm (0/1)	Same machinery supplier or technician as a T2 firm (0/1)	Discussed servomotors with a T2 firm (0/1)	Same mosque as a T2 firm (0/1)	Same machinery supplier or technician as a T2 firm (0/1)
	(1)	(2)	(3)	(4)	(5)	(6)
T1	0.016	0.001	0.044	0.028	0.002	0.040
	(0.036)	(0.043)	(0.036)	(0.029)	(0.042)	(0.033)
	[0.052]	[0.054]	[0.054]	[0.052]	[0.054]	[0.055]
T2	0.048	0.138	0.095			
	(0.046)	(0.062)**	(0.041)**			
	[0.054]	[0.052]***	[0.057]*			
Exposure (500m)	0.165	0.122	-0.023	0.240	0.085	0.031
	(0.078)**	(0.044)***	(0.097)	(0.069)***	(0.043)**	(0.128)
	[0.063]***	[0.075]	[0.098]	[0.067]***	[0.087]	[0.112]
Exp. Exposure (500m)	0.010	0.318	0.089	-0.127	0.324	0.022
	(0.119)	(0.114)***	(0.148)	(0.097)	(0.101)***	(0.187)
	[0.113]	[0.126]**	[0.154]	[0.131]	[0.143]**	[0.176]
Observations	419	449	457	281	307	313
P-value, T1=T2	0.543	0.012	0.371			
Upazila FE	Y	Y	Y	Y	Y	Y
Strata FE	Y	Y	Y	Y	Y	Y

Notes: Estimates are of equation 1 in text, but without dependent variable at baseline. Columns 1 and 4 represent a 0/1 indicator for whether the firm reported discussing servomotors with a T2 firm among other discussions on business-related activities. Columns 2 and 5 represent a 0/1 indicator on whether the firm reported going to the same mosque as at least one other firm in the information and installation treatment (T2) arm. Columns 3 and 6 represent a 0/1 indicator on whether the firm reported using the same machinery supplier, repair shop or motor technician as at least one other firm in the information and installation treatment (T2) arm. The standard errors in parentheses use the spatial correction from Conley (1999). The standard errors in square brackets are heteroskedasticity-robust (without the correction for spatial correlation). *p <0.10; **p <0.05; ***p <0.01.

Table 10: Spillover Effects of Proximity and Communication Network on Sharing of Meter Report Cards

	Including T2		Excluding T2	
	Shown report by T2 firm (0/1)	Shown report by T2 firm (0/1)	Shown report by T2 firm (0/1)	Shown report by T2 firm (0/1)
	(1)	(2)	(3)	(4)
T1	-0.007	-0.008	-0.010	-0.013
	(0.017)	(0.019)	(0.016)	(0.017)
	[0.018]	[0.018]	[0.018]	[0.018]
T2	0.007	0.007		
	(0.022)	(0.023)		
	[0.020]	[0.021]		
Exposure (500m)	0.029		0.019	
	(0.013)**		(0.008)**	
	[0.013]**		[0.010]**	
Exp. Exposure (500m)	-0.002		0.011	
	(0.013)		(0.012)	
	[0.021]		[0.011]	
Exposure, network		0.049		0.027
		(0.029)*		(0.020)
		[0.021]**		[0.018]
Exp. Exposure, network		-0.004		0.064
		(0.028)		(0.021)***
		[0.033]		[0.034]*
Observations	473	473	325	325
P-value, T1=T2	0.427	0.410		
Upazila FE	Y	Y	Y	Y
Strata FE	Y	Y	Y	Y

Notes: Estimates are of equation 1 in text, but without dependent variable at baseline. Exposure(500m) is 0/1 indicator for having 1 or more T2 firm within a walking distance of 500m. Exposure, network is 0/1 indicator for whether the firm reported talking business with 1 or more T2 firm(s). Outcome is a (0/1) indicator for whether the firm reported having seen an electricity use report card that showed electricity usage for both clutch and servo motors and was made available to the information and installation treatment (T2) arm. The standard errors in parentheses use the spatial correction from Conley (1999). The standard errors in square brackets are heteroskedasticity-robust (without the correction for spatial correlation). *p <0.10; **p <0.05; ***p <0.01.

Table 11: MVPF Calculation

	Beneficiary type			
	Adopter T2	Inframarginal T2	Spillover adopter	Total
(A) Number of beneficiaries per subsidized motor	Direct adoption causal estimate (=0.8 per subsidized motor)	T2 firms that would have adopted anyway (=1-0.8 = 0.2)	Spillover adoption causal estimate (= 1.5 per subsidized motor)	2.5
(B) Private WTP per beneficiary	PDV of electricity savings (=99)	Subsidy value (=46)	PDV of electricity savings minus cost of motor (=53)	197.9
(C) Social WTP per beneficiary	PDV of C02 averted valued using SCC (=80.3)	None	PDV of C02 averted valued using SCC (=80.3)	160.5
(D) Total WTP per beneficiary type = A*(B + C)	143.4	9.2	199.8	352.4
(E) Public cost per subsidized motor	46	46	46	46
MVPF = D/E	3.1	0.2	4.3	7.7

The calculation uses the US Environmental Protection Agency (EPA) estimate of the Social Cost of Carbon (SCC) of $193 in 2020 (EPA, 2023) and a discount rate of 2% per annum for consistency with the MVPF estimates reported in Haaland et al. (2023). New servo motors are assumed to have a life of 10 years. The estimate of the number of spillover adopters per subsidized motor, 1.5, includes first and second degree spillovers, assuming a T2 seeding rate of 1 in 3, as discussed in subsection 7. The direct adoption causal impact per subsidized motor, 0.8, is based on the main T2 impact estimate reported in table 2. Benefits from the abatement of other greenhouse gases and local pollution benefits, such as PM2.5 abatement, are not included.

Table A.1: Balance Table, Non-Attriters

	N.Obs	Control	T1	T2	P-value, Control=T1	P-value, Control=T2
	(1)	(2)	(3)	(4)	(5)	(6)
Num. of Machines						
Num. machines (total)	473	5.89	6.22	6.78	(0.42)	(0.37)
Num. machines (non-motorized)	473	0.26	0.17	0.16	(0.20)	(0.13)
Num. machines (w/ ext. motor)	473	0.19	0.19	0.26	(0.97)	(0.49)
Num. machines (w/ clutch motor)	473	4.91	4.87	5.51	(0.96)	(0.57)
Num. machines (w/ servo motor)	473	0.64	0.85	0.83	(0.42)	(0.71)
Beliefs						
Beliefs, elec usage (kwh/day) for clutch motor	473	0.65	0.67	0.70	(0.56)	(0.15)
Beliefs, elec usage (kwh/day) for servo motor	473	0.47	0.46	0.47	(0.82)	(0.96)
BDM bid ('000 BDT)	473	3.05	3.09	3.18	(0.71)	(0.60)
Beliefs, price of electricity (BDT/kwh)	473	11.18	10.93	11.03	(0.26)	(0.47)
Firm Characteristics						
Production costs, last month ('000,000 BDT)	473	0.47	0.40	0.52	(0.43)	(0.87)
Profits, last month ('000 BDT)	473	34.32	26.15	36.81	(0.44)	(0.95)
Sales, last month ('000,000 BDT)	473	0.53	0.42	0.56	(0.27)	(0.94)
Electricity costs, last month ('000 BDT)	473	5.77	4.75	5.15	(0.52)	(0.51)
Firm has Servo at Baseline (0/1)	473	0.14	0.20	0.15	(0.12)	(0.82)
Employees						
Num. employees on payroll	473	10.50	10.64	12.37	(0.88)	(0.41)
Num. permanent, full-time workers	473	9.45	9.66	10.99	(0.82)	(0.54)
Num. managers, skilled professionals	473	1.30	1.50	1.59	(0.25)	(0.11)
Num. production-line workers (total)	473	9.74	9.89	11.68	(0.87)	(0.36)
Respondent Characteristics						
Respondent is male (0/1)	473	0.96	0.98	0.96	(0.18)	(0.89)
Respondent's years of education	473	5.96	6.65*	6.64	(0.10)	(0.20)
Respondent's age	473	36.17	36.40	35.58	(0.88)	(0.45)
Respondent's experience	473	15.58	15.87	15.16	(0.75)	(0.49)
Attrited at Endline	505	0.02	0.03	0.04	(0.57)	(0.36)