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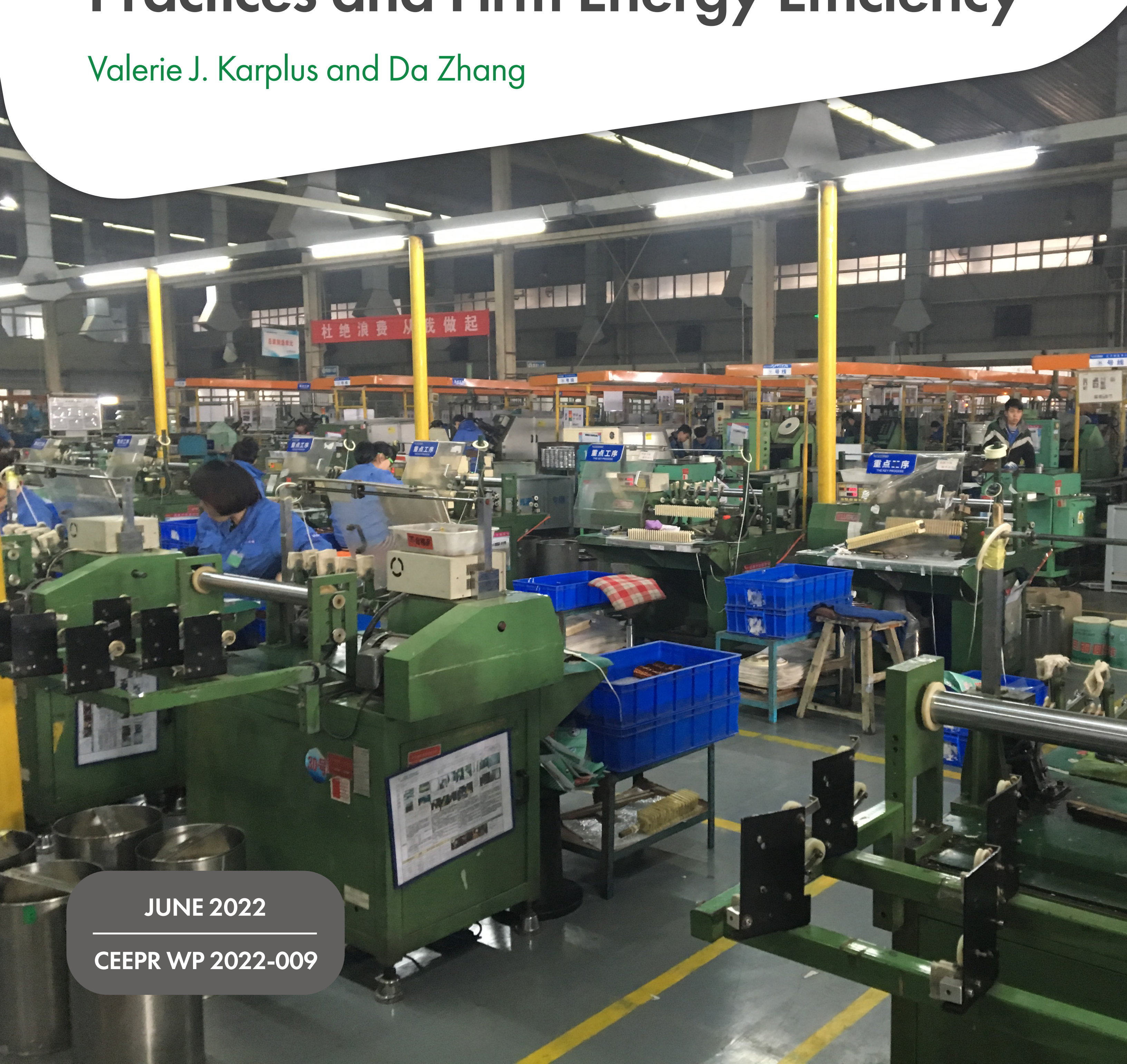

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When "Low-Hanging Fruit" Are Beyond Reach: Management Practices and Firm Energy Efficiency

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Abstract

We study whether structured management practices affect the uptake and impact of industrial energy efficiency measures, which are widely considered important for mitigating climate change. In a randomized experiment that provides small- and medium-sized metal machining firms with tailored recommendations to improve energy efficiency, we find that the likelihood of recommendation adoption increases with a firm's management practice score. However, the intervention's main effect—a reduction in the unit cost of electricity—is larger in firms with *less* developed structured practices. We find that this effect can be traced to managers' suboptimal selection of transformer-related parameters at baseline, which resulted in higher electricity costs. This "energy management gap" is most strongly associated with low monitoring, target-setting, and incentive practice scores. Our findings suggest that structured management practices may help firms absorb new ideas that are expected to reduce physical energy use and greenhouse gas emissions, while tailoring interventions to address management practice gaps in low-scoring firms may unlock opportunities to save energy cost. However, impact on greenhouse gas emissions may be limited.

Keywords: management, energy efficiency, electricity, randomized controlled trial, China

1. Introduction

Nearly every projection of what it would take to address global climate change relies heavily on industrial energy efficiency. The Intergovernmental Panel on Climate Change attributes 33% of global emissions of the greenhouse gas (GHG) carbon dioxide (CO_2) to industrial energy use, due to the fact that many manufacturing activities rely heavy on fossil fuels, especially coal, either indirectly for electricity or directly for process heat and buildings [1]. Energy efficiency has been characterized as "the most important and cost effective means for mitigating greenhouse gas emissions from industry" [2]. One recent study estimated abatement potential from industrial energy efficiency to be about five gigatons, or 10% of global emissions today [3]. Despite its anticipated importance, trends lag projected needs: the International Energy Agency's 2019 World Energy Outlook calls for a 3% annualized reduction in energy intensity, or energy use per unit of output, far from recently observed rates of 1.2% per year [4].

In response to growing pressure to mitigate climate change in recent decades, a broad range of initiatives have emerged to raise industrial energy efficiency. These initiatives include policy targets for process energy efficiency, international standards for energy management, subsidies for energy-saving investments, and training programs. Yet, despite a proliferation of initiatives, few have been studied empirically, especially in the developing world, where the benefits are expected to be large [5]. In particular, we lack evidence on how these initiatives interact with firms' internal practices and influence outcomes. Prior work has found that structured management practices are associated with higher productivity [6, 7] and superior social, including environmental, performance [8, 9, 10, 11]. However, we are unaware of any study that examines how management practices interact with an energy efficiency intervention.

We draw on prior literature in operations management and energy economics to motivate a study of how structured management practices could affect the adoption and impact of energy efficiency recommendations in firms. We test these hypotheses in the setting of a randomized controlled trial. Here, we follow common practice and include recommendations that target reductions in physical energy use as well as energy expenditure. We quantify impact in terms of both physical energy use and its unit cost. In our study, we adopt measures from [7] in which general management practices include lean operational practices, setting and monitoring progress toward production targets, and rewarding high-performing employees. We further develop a survey focused on energy management practices, which we examine as a potential mediator of the influence of general management practices on energy outcomes. Our study setting is a metal machining manufacturing cluster in Shandong

Province, China, where electricity is provided almost exclusively from coal-fired power plants, a major source of emissions of the greenhouse gas carbon dioxide (CO_2).

Our study makes three contributions. First, we experimentally quantify the impact of an energy efficiency intervention in a cluster of similar industrial firms. We study an intervention that is proposed to occupy the "locus of profitable pollution reduction" as energy efficiency reduces energy required per unit of output, potentially delivering economic as well as environmental benefits [12]. Energy efficiency has never been experimentally studied in China, with its large industrial base and unique institutional setting. We focus on two outcomes, unit energy cost and physical quantity of energy use, which are related to economic and environmental impact, respectively. While technology or process changes are expected to reduce a firm's energy needs, energy efficiency interventions may also reduce a firm's energy input costs and offset reductions or increase use. Our empirical results show that treated firms achieve savings in their unit energy cost, while there is no statistically significant impact on the quantity of energy use (and associated CO_2 emissions).

Second, we provide new insight on how firm responses to external interventions interact with their preexisting management practices, adding to prior literature on how institutional and organizational factors interact to influence firms' environmental actions and performance [13, 14, 15]. We focus on two distinct margins: adoption and impact. We hypothesize a role for baseline and cognition effects in driving each margin. We find that management practice scores are *positively* associated with recommendation adoption, but *negatively* associated with impact on unit electricity cost (and insignificantly associated with impact on energy use). We show that sub-optimal tariff selection occurred in firms with less developed structured management disciplines, especially monitoring, target setting, and incentive practices, adding to a list of factors, including energy subsidies, poor power quality, nontechnical losses, and capital constraints that distort firm energy decisions in developing countries [5]. Additional effort to overcome adoption barriers among poorly-managed firms may disproportionately unlock cost savings in ways that could contribute to both economic, and potentially also environmental, performance.

Third, our experimental setting sheds new light on the mechanism by which firms responded to interventions, revealing vast heterogeneity in responses across recommendation categories, as well as the specific management practices associated with adoption and impact. Here, our study benefits from an "insider econometrics" [16] approach: marrying detailed, interview-based evidence with measures of management practices and experimental evidence to explain the observed effects of an energy efficiency intervention. We find that the treatment effect on unit electricity cost was driven largely by one recommendation category, transformer adjustment, which resulted in larger cost reductions among firms with lower average management scores, closing an instance of the "energy management gap" [10]. Weak monitoring, target-setting, and incentive practices were most strongly associated with a higher unit cost of energy at baseline. Many of these firms were not tracking energy use and costs to begin with, which may have led them to overlook "low-hanging fruit" that high-scoring firms had already reaped.

Our analysis proceeds as follows. In Section 2, we draw on prior research to theorize how variation in structured management practices could affect the uptake and impact of an energy-efficiency intervention. Section 3 describes our empirical strategy, experimental setup, and data collection. Section 4 presents the results, while Section 5 discusses implications for the design of efforts to improve energy efficiency and mitigate climate change.

2. Management Practices and Energy Efficiency: Hypotheses

In practice, scholars have observed that many energy efficiency measures expected to be profitable are not adopted, suggesting an "energy efficiency gap" [17, 18]. Existing analyses have focused primarily on developed countries and found widespread evidence of incomplete adoption of energy efficiency measures, relative to what is projected to be profitable [19, 17, 20, 21]. Decisions in developing countries are less well understood [5]. An observational study of small and medium-sized firms in China found that very few firms had considered adopting measures to improve energy efficiency [22].

Reasons given for the energy efficiency gap include hard-to-measure costs associated with the adoption of energy-saving practices [23, 24, 25] as well as behavioral explanations [17, 26].

Beyond these factors, [27] finds that firm characteristics are important predictors of adoption. In a related study, firm performance, location, and industry correlated with participation in a generic and voluntary energy-saving program for lighting [23]. [28] find that the extent of disruption, number of prior local adopters, and strength of environmental norms influence firms' adoption of energy efficiency initiatives.

Structured management practices, which have been linked to increased productivity, may help firms to close the energy efficiency gap. A growing body of studies connects structured management practices, such as lean operational practices, target-setting and monitoring, and human resource management, to both economic [6, 7, 29, 30] and social [8, 9, 10] performance.[1] As such, structured management practices provide an example of a "fixed characteristic" that [33] may drive both economic and social performance in firms. Cross-sectional evidence shows that structured management practices are associated with lower energy and associated CO_2 emissions. [8] found that adoption of a set of structured management practices in U.K. firms was associated with a reduction in energy intensity (energy expenditure per value of output) of 17% when moving from the 25th to the 75th percentile on management score. [9] studied the relationship between "climate friendly" management practices, organizational structure, and energy efficiency in U.K. firms, and found adoption increased when the firm had an environmental manager with direct links to the CEO. A study of U.S. firms found that most management techniques were associated with lower energy intensity, suggesting that spillovers from general management practices to energy efficiency could lead to an "energy management gap" in firms with less structured practices [10].

This cross-sectional evidence leaves open the question of whether management practices affect firm responses to energy efficiency interventions. In particular, do structured management practices help managers to adopt energy efficiency measures and influence the magnitude and distribution of their impacts? Investigating these relationships is the primary contribution of our study. In the next section, we draw on prior literature to develop two sets of competing hypotheses on the magnitude of these relationships.

To develop our hypotheses, we draw on prior literature to theorize two distinct effects that

[1]Randomized controlled trials (RCTs) in India [31] and in Mexico [32] further causally relate management practices to improved economic performance outcomes.

could influence a firm's response to an energy efficiency intervention. The first is a "baseline" effect, in which reductions are greatest among firms with weak structured management practices, because the intervention reveals energy-saving possibilities that firms with stronger practices may have already exploited. This effect is similar to that found in [34], which found that firms with less developed lean practices reduced emissions more on average, because their emissions were higher to begin with. Prior cross-sectional evidence suggests firms with well-developed management practices are more energy efficient due to spillovers that limit the size of any "energy management gap" [8, 9, 10]. When presented with a fixed portfolio of energy efficiency recommendations, the baseline effect would be expected to lead to greater prior adoption of recommendations among firms with well-developed management practices and to limit potential energy savings from an intervention. As a result, the potential energy and climate change benefits of the intervention would in turn be greatest among firms with less developed management practices.

The second effect is a "cognition" effect, in which firms with well-developed management practices are more likely to adopt and realize impact from an intervention. In contrast to the baseline effect, which we hypothesize largely derives from spillovers to generic management practices, the cognition effect stems from the superior ability of well-managed firms to consciously seek and apply specialized energy management knowledge to assess the value of recommendations. There is some prior support for this idea: firms that adopt either the ISO 9000 standard or TQM are more likely to adopt the ISO 14001 standard as well [15]. On the impact margin, evidence from the literature is mixed: when it comes to the voluntary ISO 14001 environmental management system, [35] finds that adoption is largely ceremonial, while [36] and [37] find associations with environmental improvement.

While the baseline and cognition effects are not mutually exclusive, our empirical setup is designed to ask whether the baseline effect or the cognition effect dominates when it comes to adoption and impact of an energy efficiency intervention. We focus first on the adoption margin and construct two competing hypotheses:

Hypothesis #1A: Firms with a higher general management practice score are *more* likely to adopt the energy efficiency recommendations they receive.

Hypothesis #1B: Firms with a higher general management practice score are *equally or* *less* likely to adopt the energy efficiency recommendations they receive.

Turning to the question of how structured management practices could mediate an intervention's impacts, baseline and cognition effects would again be expected to work in different directions. According to our implementing partners and past empirical studies, small- and medium-sized firms in China similar to those in our study sample are unlikely to have been targeted by major energy efficiency programs and are found to lack a basic understanding of energy use in their operations [22]. We therefore anticipate that recommendations presented will represent new cost-saving opportunities for even those firms with highly structured management practices. We hypothesize:

Hypothesis #2A: Firms with a higher general management practice score will achieve a *larger* performance impact from the adoption of energy efficiency recommendations.

In this case, our alternate hypothesis is a directly competing hypothesis, positing a dominant role for the baseline effect:

Hypothesis #2B: Firms with a higher general management practice score will achieve an *equal or smaller* performance impact from the adoption of energy efficiency recommendations.

We also probe whether the effects on the adoption and impact margins are associated with specific practices, by examining relationships to management practice sub-scores for operational efficiency, target setting, monitoring, and performance-based employee incentives. Our study setting further allows us to examine the role of specific recommendations in driving the outcomes we observe.

3. Empirical Setting

3.1. China's manufacturing sector, energy use, and climate change

China uses more energy and emits more CO_2 than any other nation. Its vast and energy-intensive manufacturing sector is directly or indirectly responsible for approximately 55% of the nation's energy use [38], equivalent to more than 12% of the global total [4].[2] While much

[2]Worldwide, the manufacturing sector alone accounts for over two-thirds of end-use energy demand [4].

of this energy use is concentrated in industries with high energy intensity (iron and steel, cement, refined oil, chemical products, and mining and metals production), manufacturing activities with a higher share of value-added account for substantial energy use. Energy used in these activities primarily takes the form of electricity, an energy carrier that is generated from primary fuels. High value-added manufacturing accounts for over 12% of China's total energy use [38]. Globally and especially in China, primary fuels used to generate electricity remain dominated by fossil fuels, especially coal, which when combusted generate climate-warming CO_2 and local air pollutant emissions.

3.2. Sample selection

We worked closely with our local partner, Shandong Energy Conservation Association (SECA), in Jinan city, Shandong province (location shown in Appendix Figure A1) to select firms and implement the training. SECA is a non-governmental organization that arranges energy saving training and provides energy saving consulting for industrial and commercial firms. A team from SECA obtained a full list of actively-producing above-scale (annual revenue higher than 20 million yuan in any year between 2010 and 2015) metal machining firms in spring 2016 from eight districts/counties in Jinan city (231 firms in total). SECA then sent inquiries to all of these firms requesting consent to allow the research team to conduct an on-site interview and to collect energy use information. 110 firms agreed to receive a visit, and we successfully obtained management scores and energy use data for 100 firms. Our study involves a baseline survey of these 100 firms in 2016, followed by a randomized experiment involving a 48-firm subset of the original surveyed group, implemented between 2017 and 2020.

Firms in the sample are located within a 50-mile radius and are spread across the city's eight districts/counties, making all firms comparable on dimensions of local climate (which can substantially impact energy use), governance at the city level and above (thus policy environment is common to all firms), and market conditions (including electricity price schedules and labor force composition). Jinan city also has a distinct industrial history, as some manufacturing processes and product types have remained unchanged for thousands of years. Firms represented seven two-digit industries[3] and were chosen because electricity was their main energy source for production.

Of the original set of 100 firms for which we obtained both management scores and energy use information, we dropped two outliers, which were either involved solely in assembly (and had very low energy intensity) or reported dramatic shifts in energy intensity between 2014 and 2015. We further dropped seven firms that did not contain any of the three energy-intensive process categories related to metalworking: machining, casting, and forging. We analyze the data collected on the remaining 91 firms in the descriptive part of our analysis. Many of the firms in our sample manufacture multiple products using a fixed set of production equipment that is powered by electricity. Two-thirds of our 91-firm sample consisted of single-plant firms. Descriptive statistics for the 91 and 48 firm samples in 2015 from the baseline survey are shown in Table 1. Photographs (taken with permission) of the physical setting and production floor at several of our sampled firms are shown in Appendix Figure A2.

3.3. Baseline data collection and preparation

We collected our baseline survey over two months in March and April 2016. The two-part survey covering management and energy management was designed and administered by a collaborative team including an analyst, two associates, and one junior partner from the China offices of a global management consultancy and researchers from the Massachusetts Institute of Technology and Tsinghua University. The team administered the survey with logistical support from SECA. Over a period of five weeks, two groups (each comprised of one MIT or Tsinghua researcher and one consultancy analyst or associate) conducted on-site interviews on general management and specialized energy management practices in Mandarin Chinese at all 100 firms. Team members attended a one-day orientation on survey

[3]In common industry classification systems, e.g., the North American Industry Classification System used in the United States or the Industrial Classification for National Economic Activities used in China, each industry is designated with an industry code. The first two digits refer to major industry types. Specifically, the manufacturing industry is classified into 31 major industries in China's system, with the first two digits from 13 to 43. Firms we visited are from the following seven two-digit industries: 31 - ferrous metal smelting or rolling, 33 - metal products, 34 - general equipment, 35 - special equipment, 36 - automobile, 37 - other transportation equipment, and 38 - electrical equipment.

administration, followed by a mock interview round to ensure consistency in teams' understanding of the survey questions and scoring procedure. The teams visited two to four sites per day, depending on travel time between sites, and interviewed one member of the company's general management and, when available, one energy specialist. Completing the full interview (including its general management and energy management components) required approximately one hour.

The general management practices questionnaire followed the methodology of the World Management Survey very closely [7], with minor adjustments to localize concepts to the Chinese context. The survey included 18 questions in four categories (operations, targets, monitoring, and incentives), each of which was scored on a 1–5 scale by the interviewer. Subscores for each of the four categories are averaged to generate one general management score per firm. Scoring outcomes were not shared with the interviewee. Starting with a Chinese translation of the management survey based on [7], question translations were vetted for accuracy of meaning and potential for misinterpretation by multiple Chinese speakers within the global consultancy, MIT, and local Shandong teams. Prior to fielding the survey, the team performed a dry run of the full interview with one company. Adjustments were made to reflect managers' feedback and to shorten the energy management questionnaire to keep the entire process under one hour.

The energy management questionnaire incorporated specific practices required by China's national standard for energy management GB/T 23331, which closely follows the international energy management standard ISO 50001. Questions attempted to measure the firm's general awareness and experience with energy-saving measures, as well as the existence and extent of the company's internal energy management system. A copy of the energy management questionnaire is provided in Appendix Table A1. Both general management scores and energy management scores are calculated as unweighted averages of scores on individual questions. Scores were converted to z-scores for ease of interpretation in regression analysis.

The interview and following intervention were designed to leverage the local network of SECA. We contacted firms by sending each a letter through SECA requesting an interview and offering a free energy audit along with recommendations on how to save energy cost and use. SECA then called their main contact within each firm to schedule a visit. We initially expressed an interest in speaking with a member of the firm's leadership team, and the respondent internally nominated a firm representative to participate in the interview. Interviewers began by asking general management questions to the appointed representative. Energy management questions were typically answered by the main interviewee. In very few cases when firms had a specialized energy manager on duty, he or she also participated in the interview.

In parallel, monthly electricity use and production information was obtained through periodic surveys disseminated by SECA. We collected these data in early 2016 for the years 2013–2015 for the 91 firm sample, and for a further five years (2016–2020) for the 48 firms included in the experiment in three waves, once during the first half of 2018, again in the first half of 2019, and then again during the second half of 2021. Electricity consumption data, including physical use in kilowatt-hours and expenditure in value terms, was obtained at monthly resolution for all eight years. Firms were notified that raw data provided would be deidentified before use in our analysis. SECA is not involved in regulatory enforcement and regularly interacts with government offices at the county level as well as with firms directly, leading to a high degree of trust and raising the chances of obtaining data that represent an honest collection effort. Firms' submissions were cross-checked against metered electricity bills for a subset of firms to ensure consistency. We were unable to verify reported consumption of other energy types, which represented a modest share of the overall total. These energy types were largely used for space heating and could not be substituted by electricity. Therefore, we focus on electricity in this study. None of the firms in our 48-firm sample had any unrecorded electricity use (e.g., self-generation).

3.4. Randomized experiment

Starting with the 48 firms in the baseline sample that share the same production process, metal machining, we generated matched firm pairs as described in [39]. Firms were matched using the Mahalanobis distance, which is computed on the basis of electricity use quantities (kWh), sales (RMB), electricity intensity (in quantity terms, kWh/RMB), ratio of sales in 2015 to sales in 2013, management score, and energy management score. We randomly pick one firm from each pair as the treated firm.[4] We conduct power calculations[5] using the baseline data (for 2013 to 2015) by assuming a hypothetical reduction in energy expenditure or use for treated firms in all 12 months of the year 2015. We run 1,000 iterations and randomly drop four firms in each iteration to allow for possible sample attrition. We find that our data can detect a 3% reduction in electricity unit cost or 9% reduction in electricity use at the significance level of 10% with a probability of 80%.

With the help of SECA, we recruited local experts to perform the intervention. These experts were specialists in the types of equipment and processes used in our sample of metal machining firms. The energy efficiency treatment was administered in two waves, one running from June to August 2017, and the other from October 2017 to January 2018. Each treated firm received a one-day site visit from two experts. These experts gathered information in discussions with firm managers and then examined energy-intensive equipment and production processes for opportunities to improve. The experts then presented preliminary energy-saving recommendations and best practices for energy management to firm managers verbally at the end of the visit. Within one month of the visit, the experts followed up with a formal document that included an itemized list of energy-saving recommendations and energy management practices that were tailored to firm conditions. Two rounds of follow-up visits to evaluate adoption of recommendations were performed in spring 2018 and spring 2019, and endline surveys on electricity use for 2018 and 2019–2020 were collected in spring 2019 and fall 2021, respectively. Two treated firms and three control firms dropped out of these endline surveys due to unstable production or major business changes, leaving 43 firms for estimation of treatment effects. In fall 2021, our team also visited 18 of 21 control firms to assess the applicability and prior adoption of the same menu of recommendations, to strengthen the robustness of our analysis on recommendation adoption for the 24 treated firms.

For each recommendation, we strongly encouraged the experts to provide their best

[4]Information about our experimental protocol can be found on the American Economic Association Randomized Controlled Trial Registry at `https://www.socialscienceregistry.org/trials/2221`.

[5]"Power" refers to the probability that a test correctly rejects the null hypothesis when it is false (avoiding a Type-II error). The power calculation ascertains whether an experiment design has an acceptable level of power to detect a given treatment effect.

estimate of the available financial savings expected to result from reduced energy use for each recommendation. We also asked them to provide their best estimate of the cost of adoption (initial investment). However, our experts expressed that they found this second request difficult and very demanding. First, experts cited that equipment and material prices were highly volatile. They also indicated that the labor costs associated with adopting the recommendation were highly uncertain, making it challenging to provide an accurate cost estimate without misleading the firm. Second, for recommendations highly tailored to specific equipment and production processes, experts found estimating electricity savings more difficult, as there was no template or experience to work from. For example, an expert could suggest that insulating a furnace could save substantial energy, reducing ambient heat losses. However, if a firm had never measured the heat efficiency of the furnace (which was common in our sample), estimating the improved efficiency or cost savings was impossible. Therefore, we were only able to obtain estimated energy savings from the experts for a subset of recommendations, which we provided to firms when available. Otherwise, we indicated to the firm that an energy-saving estimate was not available. As a general rule of thumb, and to increase the likelihood that recommendations would be considered, experts focused on providing recommendations that were expected to pay back within three years.

Recommendations were categorized into six groups based on the equipment or end-use targeted for efficiency improvement. In Table 2, we summarize the number of recommendations provided to treated firms, as well as the applicability, pre-treatment adoption, and availability of information about the estimated energy savings within each of the six groups. The first five categories of recommendations are listed roughly following the order from the most bespoke to the most standard, reflecting differences in the customization required and firm's self-reported feedback on the technical and behavioral complexity of implementation. For example, most lighting system recommendations are relatively standard because they typically only involve replacing old inefficient light bulbs with more energy-efficient LEDs, while recommendations related to the configuration of the transformer are generally less standard. This category includes changing to another electricity rate plan that would be less costly for the firm. The rate plan options are the same for all firms, but the optimal electricity tariff depends on a firm having a detailed understanding of its own patterns of energy use.

Specifically, making the most of a rate plan update further requires firms to optimize their own parameters, e.g., transformer capacity or maximum load, which must be reported to the local utility company. This category of recommendations explicitly targets unit electricity cost. Recommendations grouped in the category "others" target energy-intensive equipment that is uncommon or belongs to specific vintages, e.g., a decoiler machine or a shot blasting machine. A manager would need to locate customized parts or components if she wished to retrofit the equipment. An example of recommendations provided to one of the firms in our sample is shown in Appendix Table A2.

4. Results

4.1. Impact of the energy efficiency intervention

We begin by presenting the causal impacts of the energy efficiency intervention, before turning to the role of structured management practices. Following the intervention, we document a high level of adoption among treated firms. As shown in Figure 1, the likelihood of an applicable recommendation being adopted ranged from 0.4 (for other equipment) to 0.9 (for lighting) at our second follow-up visit.[6]

Although consultants based their evaluations on a consistent set of recommendations, not all recommendations were equally applicable for every firm. For example, not every firm had a furnace or air compressor, and three out of 24 firms shared a transformer, constraining potential transformer adjustments. Before our training, some recommendations had already been adopted previously. At the time of the second follow-up visit after the treatment, aside from lighting recommendations, which had an adoption rate of 90%, it is noteworthy that adoption rates for other categories were between 40% to 70%. This is despite the fact that the consultants provided advice to firms on tailoring recommendations to their production conditions and that recommendations were expected to pay back within a maximum of three years.

[6] Within each category, adoption likelihood is calculated as the number of firms that adopted a recommendation divided by the number of firms for which it is applicable (including those who received it as part of the treatment plus those who had previously adopted it).

We estimate the treatment effect on the firms' electricity unit cost or use with the following specification:

$$log(y_{im}) = \alpha_0 + \beta_1 t_m \times treatment_i + \gamma_{\mathbf{i}} + \tau_{\mathbf{t}} + \varepsilon_{im}, \quad (1)$$

where the dependent variable $log(y_{im})$ denotes the log unit cost (yuan/kWh) or quantity (kWh) of firm i in month m. The binary variable t_m is the treatment status, equal to 1 for post-treatment months and zero otherwise. The binary variable $treatment_i$ indicates whether or not a firm is in the treatment group. The treatment effect is estimated by the coefficient β_1. $\gamma_{\mathbf{i}}$ and $\tau_{\mathbf{t}}$ are firm fixed effects and time (month) fixed effects, respectively. Results are displayed in columns 1 (for unit cost) and 2 (for quantity) of Table 3.

Columns 3–6 further explore the interaction between treatment effects and management scores using the following specification:

$$log(y_{im}) = \alpha_0 + \beta_1 t_m \times treatment_i + \beta_2 t_m \times treatment_i \times mgmt\_zscore_i + \gamma_{\mathbf{i}} + \tau_{\mathbf{t}} + \varepsilon_{im}, and \quad (2)$$

$$log(y_{im}) = \alpha_0 + \beta_1 t_m \times treatment_i + \beta_2 t_m \times treatment_i \times tp/bm\_mgmt\_zscore_i + \gamma_{\mathbf{i}} + \tau_{\mathbf{t}} + \varepsilon_{im} \quad (3)$$

where $mgmt\_zscore_i$ is the management z-score, and $tp/bm\_mgmt\_zscore_i$ is a dummy represents whether a firm has a management z-score in the top quartile (high-scoring) or the bottom quartile (low-scoring). β_2 is the estimated interaction between treatment effects and management scores. In columns (7) and (8), we zero in on the effect of the adoption of transformer-related recommendations. Column (7) interacts treatment timing with treatment group and a transformer adoption dummy that equals 1 for firms that adopted the transformer-related recommendation and zero otherwise. Column (8) shows the result of the local average treatment effect (LATE) estimation using an instrumental variable regression specification based on equation 2. Here, $treatment_i$ now equals 1 for firms that adopted the transformer-related recommendation and zero otherwise. It is instrumented by a binary variable indicating whether or not a firm is in the treatment group. If we consider that the treatment effect on the unit cost is mainly driven by the adoption of transformer-related recommendations, the treatment effect estimated in column (1) can be considered an intent-to-treat (ITT) effect. This approach is similar to experimental settings in [25] and [40].

In terms of estimates of average impact on all the firms that received treatment, we find that our energy efficiency intervention reduced firms' average unit cost of electricity but did not significantly change electricity use. We focus on firms' post-treatment unit electricity cost changes as the main effect of our intervention. On average, a treated firm experienced an 8% decline in its unit cost (statistically significant at the 5% level, see column (1) in Table 3).[7] While noteworthy, it is perhaps unsurprising that our intervention did not affect total electricity use, because it imposed no limit or disincentive. Instead, because firms could have adjusted their inputs and/or production levels in response to the new information, the predicted effect on total physical electricity use is ambiguous (see Appendix Section A1 for an explanation, based on a simplified analytical model).

We conduct robustness checks to validate our results for the log unit cost treatment effect using the [41] procedure and a permutation-based test, as described in greater detail in [42]. First, [41] propose a robustness test that is useful for small samples with a large number of repeated observations, as is the case in our setting. Based on [41], we first estimate the effect for each firm separately, and then conduct a standard t-test to compare the grouped means between the treated firms and the control firms. This method requires that the firm-by-firm parameter estimates be independent and distributed Gaussian, which can be justified by the large number of repeated observations. The p-value of the Ibragimov-Mueller t-test is 0.02, supporting the robustness of our results.

Second, we use a permutation-based test that uses the Wei-Lachin statistic as described in [43]. Our data set for the impact evaluation included 22 treated firms and 21 control firms. If the null hypothesis of no treatment effect is true, each possible candidate value of the Wei-Lachin statistic will occur with the same probability, regardless of which 22 firms among the 43 are treated. To establish the empirical distribution of the Wei-Lachin statistic, we conduct 1,000 permutations that randomly assign 22 treated firms and 21 control firms and calculate the Wei-Lachin statistic for each permutation. We therefore could compute a critical value of the permutation-based test, and reject the null hypothesis if the real Wei-

[7]When the data series is extended to 2020, the treatment effect is still visible, as shown in Appendix Table A3. The data during 2020 are noisier due to the impact of COVID-19 on firm production schedules. We focus on treatment effects estimated through the end of 2019.

Lachin statistic exceeds the predicted value for its corresponding quantile. The calculated critical value is 0.03 (<0.05), so we reject the null hypothesis at the significance level of 5%.

We also plot an event study graph showing unit cost and total electricity use outcomes by time for treated firms relative to control firms in Figures 2a and 2b, respectively (using equation 4 for estimation). The effects by time can also be observed by looking at the trends after the treatment (see Appendix Figure A3).

$$log(y_{im}) = \alpha_0 + \sum_{n=-48}^{24} \beta_n \times (I_{im}^n \times treatment_i) + \gamma_{\mathbf{i}} + \tau_{\mathbf{t}} + \varepsilon_{im}, \tag{4}$$

where I_{im}^n is a dummy variable. If the gap between the month of observation m and the time of receiving the treatment for firm i is n, I_{im}^n equals 1; otherwise, it equals 0. Other variables are defined similarly to those in equation 1. We take one month before receiving the treatment as the reference period, enabling us to observe the differences in unit cost and total electricity use between treated firms and control firms in other periods compared with the reference period.

4.2. Management practices and adoption (Hypothesis #1)

Above we show that our intervention's main effect can be quantified in terms of a statistically-significant reduction in unit electricity cost of approximately 8% on average.[8] We now turn to separately examine how management practices interact with both adoption and impact. For each margin, in order to illuminate the net contribution of the cognition and baseline effects, we focus first on characterizing the pre-treatment relationship between management practice scores and both adoption and unit cost outcomes.

4.2.1. Pre-treatment baseline effect: Adoption

We use multiple measures to probe the pre-treatment adoption status of the recommendations included in our intervention. Immediately prior to introducing the treatment, we surveyed the pre-treatment adoption status among the treated firms. We provide granular data on recommendation applicability and adoption in Table 2. Comparing column (2) in panels

[8] All treatment effects are reported in log points.

(b) and (c), the number of firms (out of 12) adopting each category of recommendation prior to training was similar among firms with above-median versus below-median management scores. At the end of 2021, we visited 18 of the firms in the control group, provided them with applicable recommendations, and asked about their "pre-treatment" adoption status of these recommendations, which allowed us to explore the management-adoption relationship before receiving our treatment in a larger sample size. The lack of a relationship between management score and pre-treatment adoption is supported by the insignificant coefficient on management score in pre-treatment regressions, shown in Appendix Table A4 for both the 24-firm sample (treated firms only) and the 42 firm sample (24 treated firms plus 18 control firms).

Taken together, we find no empirical support for a difference in firms' self-declared pre-treatment adoption of the recommendations in our intervention when comparing firms with high and low management practice scores. This is consistent with prior studies that find a limited awareness of energy efficiency measures among firms in developing countries [22, 5]. In an endline survey, we asked managers if the firm had received energy-related consulting or advice within the last five years, and no respondent answered yes. However, it is possible that there may still be unobserved differences in the adoption of energy-efficient practices among firms as a function of management practice scores.

4.2.2. Estimating the management-adoption relationship

We estimate the relationship between management practices and adoption by regressing post-treatment adoption for treated firms (with and without a series of controls) on management practice scores. Table 4 shows the coefficient estimates of OLS regressions that examine the correlation between general management scores and adopting a recommendation (or receiving energy-saving estimate) using the following specification:

$$Dependent_{ij} = \alpha_0 + \beta_1 mgmt\_zscore_i + \mathbf{X_i}\beta + \gamma_{\mathbf{j}} + \varepsilon_{ij}, \tag{5}$$

where $Dependent_{ij}$ equals 1 if the recommendation in category j provided to firm i is adopted (or with energy-saving estimate) and zero otherwise.[9] $mgmt\_zscore_i$ is the management z-score or management sub-zscores (operations, monitoring, targets, and incentives), $\mathbf{X_i}$ denotes firm control variables, including firm size, firm age, and state ownership dummy, and $\gamma_{\mathbf{j}}$ denotes recommendation category dummies.

We find that our management measure is positively and significantly associated with adoption, consistent with a dominant role for the cognition effect, supporting Hypothesis #1A. Column (1) and (2) of Table 4 show that a one standard deviation increase in management score increases the probability of adoption by 20–23 percentage points, and is statistically significant at the 5% level. Controlling for recommendation category, we find a significantly higher probability of adopting recommendations that required the least customization (lighting and furnace recommendations), compared to the omitted group, other equipment, which required the most customization among the categories (see Figure 1, "Other equipment" panel). These results are in agreement with the raw data, reported in Table 2, Panels B and C, which shows better-managed firms have higher rates of post-treatment adoption (column (6)).

One potential channel by which management practices could influence adoption is if the practices increased managers' awareness and access to data about energy use, which was an important input to the consultants' calculations of the energy savings available for a firm-recommendation pair. Column (3) of Table 4 shows that on average, a one standard deviation change in management z-score was associated with a 19% increase in the probability of receiving an energy-saving estimate for a particular recommendation category. Beyond documenting a common positive relationship with management practices, we are not able to distinguish the effect of receiving an energy-saving estimate from the effect of management practices on adoption.

[9] A recommendation for a category is considered adopted if a firm self-reported implementation of any of measures in this category provided by the consulting team.

4.2.3. Adoption: The role of specific practices

Finally, we consider whether specific management practices are correlated with recommendation adoption, by replacing the general management score with each management sub-score in the regressions predicting adoption in Table A5. Here, we find that monitoring, targets, and incentives (human resource practices such as performance-based pay and promotion) are all positively correlated with adoption. There is no significant relationship for lean operational practices, although the coefficient is also positive. Appendix Figure A4 shows the contribution of each sub-score using a random forest method similar to [11], which further affirms the importance of monitoring and only a minor role of lean practices. This is consistent with prior findings that lean practices are not associated with improved environmental performance [11, 8]. This is also consistent with cross-sectional evidence that lean measures are uncorrelated with energy intensity in [8]. That being said, we caution against generalizing from our unit cost results, which are driven by the transformer adjustment recommendation in our study, to recommendations that primarily reduce the energy use associated with a particular process or equipment type.

4.3. Management practices and recommendation impact (Hypothesis #2)

Next, we examine the relationship between management practices and firm energy outcomes. The impact margin can be conceptualized as the actual change in energy use or unit energy cost that resulted from any technical, process, or behavioral changes undertaken by the organization. In most settings, it is extremely challenging to obtain measures of the latter. Adoption is often interpreted as leading to energy savings that were calculated *ex ante* but rarely measured *ex post*. Our setting allows us not only the measure impact *ex post* but to use the detailed operational data we collect to localize it to specific recommendations and associate them with particular management disciplines.

4.3.1. Pre-treatment baseline effect: Impact

As in the case of adoption, we are able to obtain a measure of the baseline effect from our observational data. We examine the pre-treatment correlation between management score and both electricity unit cost and use with the following specification:

$$Dependent_{it} = \alpha_0 + \beta_1 mgmt\_zscore_i + \mathbf{X_i}\beta + \tau_\mathbf{t} + \varepsilon_{it}, \tag{6}$$

where the dependent variable $Dependent_{it}$ is either electricity unit cost or quantity of electricity use of firm i in time period t, $mgmt\_zscore_i$ is the management z-score or management sub-zscores (operations, monitoring, targets, and incentives), $\mathbf{X_i}$ denotes firm control variables, including firm size, age, and state ownership dummy, and $\tau_\mathbf{t}$ denotes time (month) dummies. Results are shown in Table 5. We find evidence of a baseline effect for electricity unit cost: a one standard deviation change in management score is associated with a 7% lower unit cost of electricity prior to treatment (see column (1)). We find no significant relationship between management score and electricity use prior to treatment (see column (2)). Subsequently, we focus on the unit cost results. To explore the robustness of our results, we exploit our 91 firm sample, shown in Appendix Table A6. We find patterns are similar.

4.3.2. Estimating the management-impact relationship

Focusing on the impact of our treatment on unit cost, we turn to column (3) in Table 3. The interaction term of treatment with management z-score is positive and significant at the 10% level, providing weak evidence that the baseline effect dominates the cognition effect.[10]. Limiting the interaction to just the bottom quartile of low-scoring firms, we find that this group is largely responsible for the unit cost effect, driving the overall unit cost reduction (significant at the 1% level): on average, firms in the bottom management quartile realized a unit cost reduction of 13% on average (column (5)), which is statistically significant at the 5% level. Being in the top management quartile, by contrast, was not associated with any unit cost reduction (column (6)).

To examine whether specific recommendation categories were responsible for the effect

[10]We see no significant coefficient on the same interaction term on the quantity regression in column (4).

we observed, we interacted a dummy for adoption of recommendations in each category with treatment status. We found that the observed effect ran almost entirely through one recommendation category, transformer adjustment, the effect of which was a 16% reduction in electricity unit cost on average (column (7)). This is consistent with the magnitude of the local average treatment effect (LATE) reported in column (8), which captures the impact of an adopted recommendation on average across all firms, consistent with transformer adjustments as the primary driver of the unit cost change.

While the study team could not have anticipated that transformer adjustment would be the recommendation category with the greatest impact when we designed the training, in hindsight our interviews with firms and deeper examination of the adoption data provide some insight into why it proved so important. Transformer adjustment in practice could involve one of three actions: (1) purchasing a new transformer more closely matched to the firm's maximum load, (2) optimizing transformer configuration (in cases where firms had multiple transformers) to use only those matched to maximum load, and (3) calling the grid company and reporting maximum load more accurately, so that the grid company could adjust the fixed portion of the tariff accordingly (many firms were paying on the basis of higher maximum load than they were actually using. As shown in Appendix Table A7, firms paid a fixed fee in proportion to either transformer capacity or reported maximum load (a firm can choose either of these two fee bases). A firm could simply lower this tariff by taking the third option and more accurately reporting their maximum load. This option was by far the easiest of the three for most of the firms in our sample. Many of them immediately requested the recommended adjustment. Given that these changes would be expected to take effect immediately, it is perhaps not surprising that the unit cost impact of the treatment quickly became visible in the event study figure (see Figure 2a).

Localizing the effect of the treatment to one recommendation that was widely adopted and saved cost helps us to understand why we see opposite patterns for adoption and impact in terms of the role of the baseline and cognition effects. The reason is that although firms with higher management scores had not knowingly adopted specific recommendations, they were operating closer to the recommended optimum than the low-scoring firms. The transformer adjustment recommendation was applicable to both groups when the consultants presented it, but the high-scoring firms had already reaped the "low-hanging fruit" of adjusting their transformer size, while the low-scoring firms had not. Thus, the intervention served to close a gap that resulted from an inefficiency that was easily rectified and resulted in lower energy cost, but with no detectable change in absolute energy use (or associated GHG emissions). When we examine the correlation between management scores and electricity unit cost or use in 2019 and 2020 (about two years after the intervention), we no longer find a significant relationship, as shown in Appendix Table A8. Our setting suggests that it may take greater effort to encourage firms to take up energy-saving interventions that are further from the "locus of profitable pollution reduction," an idea we return to in the final section.

4.3.3. Impact: The role of specific practices

As in the case of adoption, we can investigate whether specific management practices are associated with the treatment effect on unit cost using the following specification:

$$log(y_{im}) = \alpha_0 + \beta_1 t_m \times treatment_i + \beta_2 t_m \times treatment_i \times mgmt\_sub\_zscore_i + \gamma_{\mathbf{i}} + \tau_{\mathbf{t}} + \varepsilon_{im}, \quad (7)$$

where $mgmt\_sub\_zscore_j$ is management sub-zscore (operations, monitoring, targets, and incentives). Results are shown in Table A9. We find that monitoring practices have the strongest association, although targets and incentives also show weakly significant relationships. Lean operations practices are uncorrelated with the observed unit cost reduction, consistent with our observations for adoption. Similar to the adoption margin, we find that higher monitoring, target-setting, and incentive practice scores are associated with smaller treatment effects. Pre-treatment correlations suggest a strong role for the baseline effect for monitoring, target-setting, and incentive practices, as shown in Appendix Table A10.

4.4. Evidence of mechanism

Why might better generic management practices lead firms to be both more likely to adopt recommendations and to lead to more limited benefits of an energy efficiency intervention? Prior studies have found that firms with stronger general management disciplines are also likely to have developed specialized practices [15]. We examine correlations between our generic and energy-centric management practice measures in Appendix Table A11. We find strong positive correlations between general management practice scores and multiple measures of energy management, including energy management practice scores derived from the average of ten questions in our baseline energy management survey (0.53), whether or not the firm has adopted standards (0.42), whether the firm has a dedicated energy management team (0.43), and whether the firm has adopted energy-saving targets (0.35). The latter three yes-or-no questions are not subjective questions and help to alleviate concerns about the potential for common method bias when examining the relationship between general management scores and energy management scores, which were generated on a single firm visit. Firms may have endogenously developed energy management capabilities to limit the impact of energy cost on their economic performance. These firms' energy-centric practices may also have translated into receptivity to recognize the value of energy-related advice from the consulting team and incorporate it into organizational routines, explaining the higher rates of adoption among better-managed firms.

One remaining puzzle is why firms with higher management scores did not differ in their pre-treatment adoption of the recommendations offered. One potential reason is that managers may have felt very limited to no external pressure to limit energy use for its own sake or for environmental reasons. Well-developed management practices in this context may have simply increased firms' awareness of cost-saving opportunities, including those related to energy, supporting the existence of spillovers from generic management practices. Nearly all of the electricity unit cost gap we measure is due to a discrepancy in transformer sizing or in the firm's reported and actual peak load. As shown in Table 2, only four firms were aware of transformer adjustment and had previously adopted relevant measures. This evidence is consistent with a role for management in helping firms to reap the "low-hanging fruit" of reducing energy cost, but with no tangible impact on physical energy use or related emissions. Our study suggests that management practices do not automatically support sustainability outcomes. In the absence of constraints on pollution, they may help firms reduce energy expenditures in ways that are aligned with overall cost efficiency, but will not necessarily deliver environmental impact.

5. Conclusion

Our results provide new evidence on how a firm's structured management practices affect the uptake and impact of an energy efficiency intervention. These findings advance prior work in several ways: (1) by using an experimental setup in which access to a tailored energy efficiency intervention is exogenous, permitting causal estimation of its effects on firms; (2) by quantifying the interaction of the treatment's adoption and impact with structured management practices in a relatively homogeneous, collocated set of firms; and (3) by exploring which practices drive the pre-treatment relationship between management practices and energy outcomes and which recommendations contribute most to the observed impacts. Our findings respond to calls for experimental evidence of how energy efficiency interventions interact with firm practices and energy outcomes in emerging market settings [9, 5]. Below, we discuss the major implications of our findings for the design and targeting of energy efficiency interventions and for the potential of these inventions to contribute to mitigating climate change.

First, our results suggest the importance of understanding drivers of firm heterogeneity prior to an intervention and reflecting it in the recommendations provided. We find that firms with lower management scores report higher a unit cost of electricity at baseline and that this gap closes after our intervention. Collecting information about firm's management practices at baseline could help identify those firms that may be less optimized prior to the intervention, improving the targeting and tailoring of recommendations. Recommendations to firms with low management scores could include management practices as well as energy management disciplines, which could complement specific process- and equipment-oriented recommendations. For example, firms could be directed to install energy metering equipment and hold regular meetings to evaluate energy performance metrics. These steps would be expected to unlock energy cost efficiencies, benefiting firms economically and potentially increasing recommendation acceptance.

Second, our findings show that impact can be highly uneven across recommendations. The menu of recommendations in our setting closely resembles real-world energy auditing and consulting services that target both higher energy efficiency and lower energy expenditures. The impact on unit energy cost of recommendations in our menu was found to be driven by a single recommendation category, transformer adjustment. Adjustments reduced the cost of electricity mechanically, which by itself would be predicted to increase energy use and increase greenhouse gas emissions. The effect on unit cost due to this recommendation category may have been so large that it obscured any effect of other recommendations in improving energy efficiency and/or reducing energy use. This finding underscores the importance of considering heterogeneous and interactive effects of the various components of energy efficiency interventions.

Third, our findings suggest that despite high expectations for energy efficiency to reduce firms' energy-related CO_2 emissions [2, 3, 4], energy efficiency interventions may preferentially deliver energy cost savings but limited physical use reduction, especially in emerging market settings, by narrowing the "energy management gap." A firm's emissions of CO_2 are a function of output scale, energy use quantity, and the CO_2 intensity per unit of physical energy used [44]. However, real-world interventions frequently target a combination of energy use quantity and energy cost. In settings such as ours where energy efficiency information and incentives are generally low, and there is limited external pressure to reduce physical fossil energy or greenhouse gas emissions (e.g., by pricing carbon), the effects of implementing cost-saving recommendations may dominate, because they are expected to provide the greatest private benefit to firms.

Our findings support the notion that whether or not management practices function as a "fixed characteristic" [33] that can drive both economic and environmental performance may depend on a firm's broader objectives and institutional constraints. Energy efficiency interventions, even for firms with well-developed management practices, are unlikely to be a silver bullet on their own. Our adoption results suggest that structured management practices may increase managers' willingness and ability to try out recommendations that are potentially economically and environmentally beneficial, providing them with a latent capability to save energy. More research is needed to understand whether a price or binding constraint on CO_2 emissions would encourage adopters to realize more of the available energy saving potential, expanding the "locus of profitable pollution reduction" [12]. In this respect, internal practices and external constraints could work in tandem to enable firms to reduce

CO_2 emissions while limiting negative impacts on overall firm performance.

Table 1: Descriptive statistics for the 91 (full) and 48 firm (experiment) samples in 2015 from the baseline survey.

	(1) **Full sample** **91 firms**	**(2)** **Treatment** **24 firms**	**(3)** **Control** **24 firms**	**(4)** **Treatment-Control mean difference**
Sales (million yuan)	269	150	143	6.76
	(681)	(245)	(287)	(77.0)
Sales in 2015/sales in 2013	1.0	1.0	1.0	0.0
	(0.4)	(0.3)	(0.5)	(0.1)
Electricity use (GWh)	5.8	4.2	2.8	1.4
	(18.6)	(7.3)	(5.8)	(1.9)
Electricity intensity (kWh/yuan)	0.03	0.04	0.03	0.01
	(0.04)	(0.04)	(0.03)	(0.01)
Unit cost of electricity (yuan/kWh)	0.9	0.9	0.9	0.0
	(0.2)	(0.2)	(0.3)	(0.1)
Management score	3.0	3.0	2.9	0.2
	(1.0)	(1.1)	(1.1)	(0.3)
Energy management score	1.9	2.0	1.9	0.1
	(1.1)	(1.1)	(1.2)	(0.3)

Notes. Mean and standard deviation (in parentheses) are reported for each variable.

Table 2: Summary of recommendations for treated firms.

(a) Panel A: All treated firms (24 firms)

Recommendation category	**(1) No. of firms that were applicable**	**(2) No. of firms that adopted before training**	**(3) No. of firms that received recommendation**	**(4) No. of recommendations**	**(5) Energy-saving estimate (%)**	**(6) Adoption upon receiving(%)**
Rescheduling	11	4	7	7	86	57
Transformer	21	4	17	17	59	65
Air compressor	16	1	15	15	87	67
Furnace	13	0	13	13	62	69
Lighting	24	14	10	10	90	90
Other Equipment	N/A	N/A	15	23	48	43

(b) Panel B: "Well-managed" firms (12 firms)

Recommendation category	**(1) No. of firms that were applicable**	**(2) No. of firms that adopted before training**	**(3) No. of firms that received recommendation**	**(4) No. of recommendations**	**(5) Energy-saving estimate (%)**	**(6) Adoption upon receiving (%)**
Rescheduling	6	2	4	4	100	100
Transformer	10	3	7	7	57	71
Air compressor	9	0	9	9	89	89
Furnace	6	0	6	6	83	100
Lighting	12	5	7	7	100	100
Other Equipment	N/A	N/A	8	16	69	56

(c) Panel C: "Poorly-managed" firms (12 firms)

Recommendation category	**(1) No. of firms that were applicable**	**(2) No. of firms that adopted before training**	**(3) No. of firms that received recommendation**	**(4) No. of recommendations**	**(5) Energy-saving estimate (%)**	**(6) Adoption upon receiving (%)**
Rescheduling	5	2	3	3	67	0
Transformer	11	1	10	10	60	60
Air compressor	7	1	6	6	83	33
Furnace	7	0	7	7	43	43
Lighting	12	9	3	3	67	67
Other Equipment	N/A	N/A	7	7	0	14

Notes. For each recommendation category, we show the number of firms that this category could be applied to, the number of firms that already adopted it before training, the number of firms that received it, the number of recommendations that firms received (for "other equipment" recommendation category, firms could receive more than one recommendation), percentage of recommendations that had cost estimate, and percentage of received recommendations finally adopted by firms. Panel A shows results for all treated firms, and Panel B (Panel C) shows results for "well-managed" ("poorly-managed") firms that have management scores higher (lower) than the median.

Table 3: Treatment effects on the electricity unit cost or use (quantity), and interactions with management.

	(1) Log(unit cost) (ITT)	**(2) Log(quantity)**	**(3) Log(unit cost)**	**(4) Log(quantity)**	**(5) Log(unit cost)**	**(6) Log(unit cost)**	**(7) Log(unit cost)**	**(8) Log(unit cost) (LATE)**
Treatment * After treatment	-0.08**	0.10	-0.08**	0.11	-0.04	-0.10**	-0.01	-0.19**
	(0.04)	(0.14)	(0.04)	(0.14)	(0.03)	(0.04)	(0.03)	(0.08)
Treatment * After treatment * Mgmt z-score			0.05+	0.06				
			(0.03)	(0.07)				
Treatment * After treatment * Bottom mgmt quartile					-0.13***			
					(0.05)			
Treatment * After treatment * Top mgmt quartile						0.01		
						(0.01)		
Treatment * After treatment * Transformer adoption							-0.16***	
							(0.05)	
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firms	43	43	43	43	43	43	43	43
Observations	3,602	3,602	3,602	3,602	3,602	3,602	3,602	3,602
R^2	0.44	0.89	0.45	0.89	0.46	0.44	0.46	0.46

Notes. This table reports the treatment effects estimations using specifications described in section 4.1. Standard errors are clustered at the firm level and reported in parentheses below coefficients.

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{+}p < 0.1$.

Table 4: Correlation between management and recommendation adoption

	(1) Adoption	(2) Adoption	(3) Energy-saving estimate
Management z-score	0.23***	0.20**	0.19***
	(0.05)	(0.07)	(0.06)
Recommendation category control	No	Yes	Yes
Rescheduling		0.15	0.47**
		(0.15)	(0.18)
Transformer		0.25	0.16
		(0.18)	(0.18)
Air compressor		0.22	0.39**
		(0.17)	(0.16)
Furnace		0.31**	0.21
		(0.15)	(0.17)
Lighting		0.40**	0.44***
		(0.15)	(0.16)
Log(revenue)		0.04	-0.12**
		(0.07)	(0.05)
State ownership control	No	Yes	Yes
Firm age control	No	Yes	Yes
Firms	24	24	24
Observations	85	85	85
R^2	0.20	0.30	0.25

Notes. This table reports the results from OLS regressions examining the relationship between management scores and adopting a recommendation or receiving energy-saving estimate. Column (1) shows the correlation between management and adoption without control variables. Columns (2) and (3) show estimations with consistent control variables. Standard errors are clustered at the firm level and reported in parentheses below coefficients.

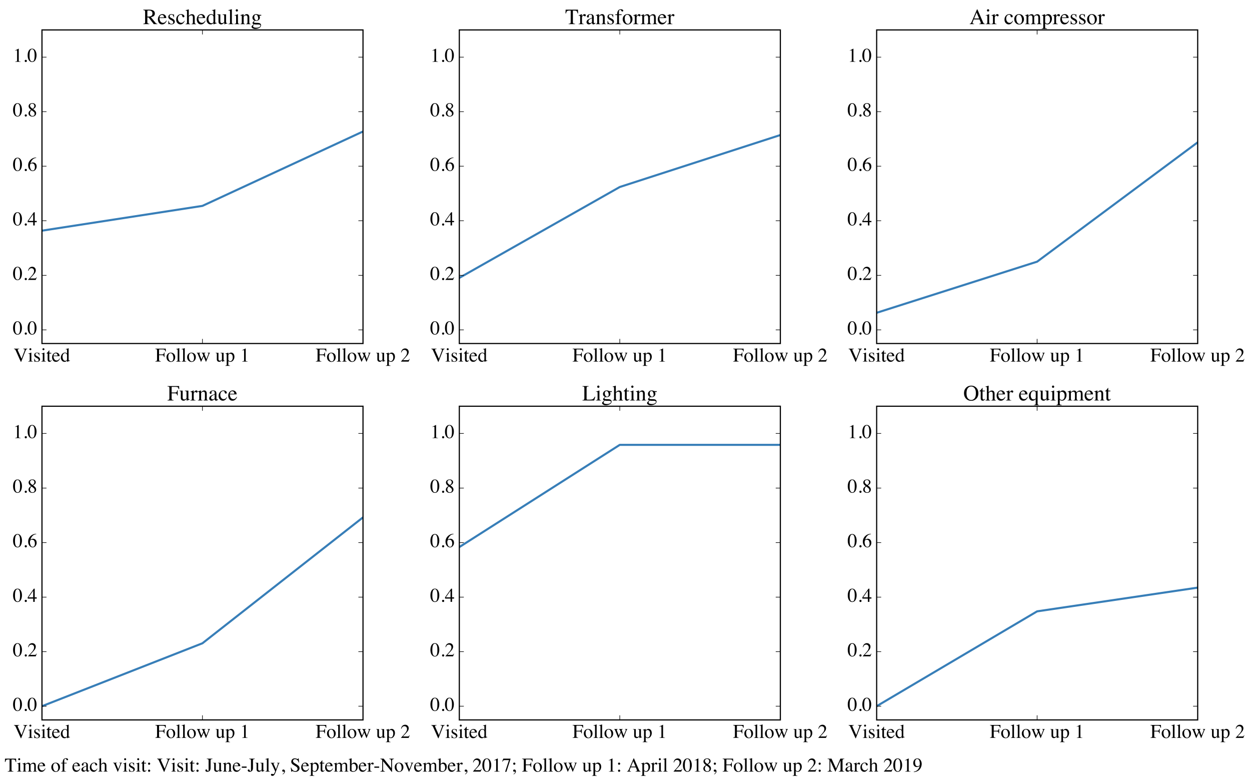
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{+}p < 0.1$.

Table 5: Correlation between management and pre-treatment electricity unit cost or use (quantity) for experiment sample (48 firms, monthly data from 2013 to 2015)

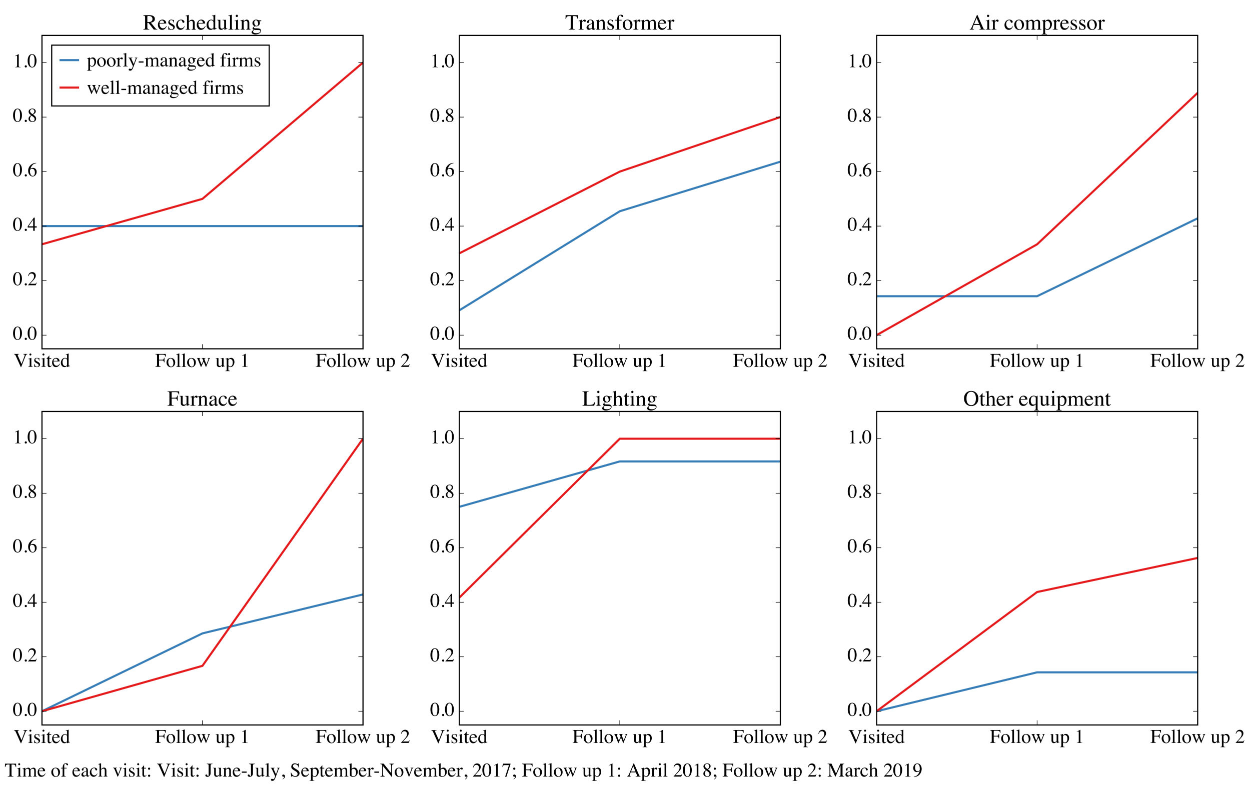
	(1) Log(unit cost) (yuan/kWh)	**(2) Log(quantity) (kWh)**
Management z-score	-0.07**	-0.11
	(0.03)	(0.16)
Treatment	-0.01	0.05
	(0.05)	(0.26)
Log(revenue)	0.03	0.77***
	(0.03)	(0.14)
State ownership control	Yes	Yes
Firm age control	Yes	Yes
Month control	Yes	Yes
Firms	48	48
Observations	1,718	1,718
R^2	0.10	0.53

Notes. This table reports the pre-treatment correlation between management scores and electricity unit cost or quantity using equation 6. Standard errors are clustered at the firm level and reported in parentheses below coefficients.

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{+}p < 0.1$.



(a) All experiment sample



(b) Well-managed firms vs. poorly-managed firms

Figure 1: Adoption share by different categories of recommendations (considering all firms that are applicable) over time.

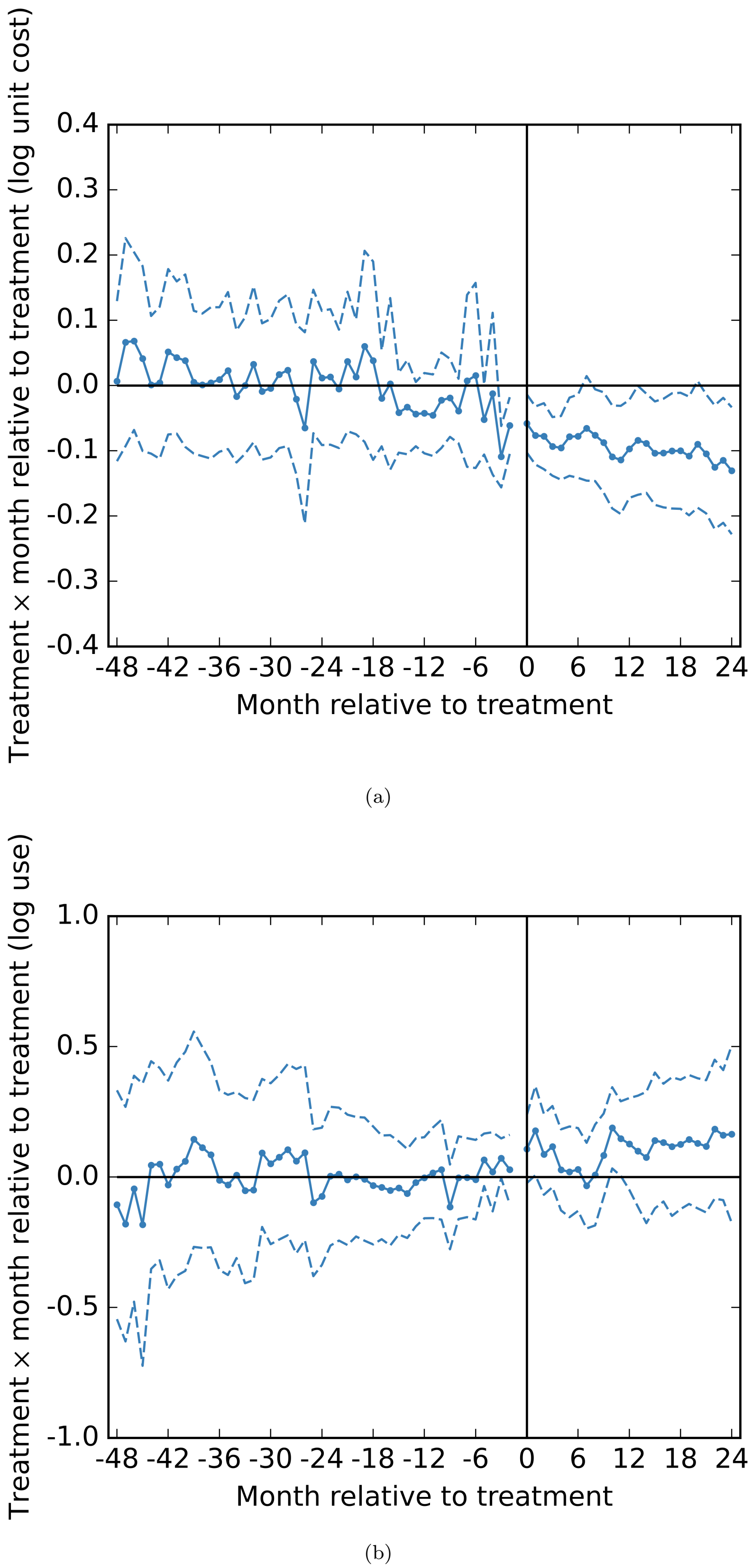


Figure 2: Treatment effects on firms' unit cost of electricity (a) and electricity use (b).

Notes. The figure shows treatment effect by time using equation 4. The month before the treatment is omitted as the reference month. Solid lines represent estimated coefficients of interest, and dashed lines represent 95% confidence intervals.

Supplementary Online Appendix

A1. Expected treatment effects

Following [45] and [46], we assume a firm faces a downward-sloping demand for its output $Q = Bp^{-\epsilon}$, where p is the output price and ϵ is the price demand of elasticity. The firm produces a physical output using energy (E) and a composite non-energy input (X), with a constant elasticity of substitution (CES) function $Q = [(A_X X)^\rho + (A_E E)^\rho]^{1/\rho}$, where $\rho = \frac{\sigma-1}{\sigma}$, σ is the elasticity of substitution between two inputs ($\sigma > 0$, $\rho < 1$), and A_E and A_X are the energy productivity and the specific productivity for other inputs, respectively.

The firm chooses the quantity of X and E to maximize its profit function, given that the price of energy input is p_E and the price of other inputs is normalized to 1:

$$\pi = pQ - X - p_E E = B^{1/\epsilon}[(A_X X)^\rho + (A_E E)^\rho]^{\phi/\rho} - X - p_E E,$$

which has a unique solution given that the production function has a decreasing return to scale under the standard assumption $\epsilon > 0$ ($\phi = \frac{\epsilon-1}{\epsilon} < 1$).

Using first-order conditions, we can obtain the energy demand:

$$E = Q[A_X^{-\frac{\rho}{\rho-1}} A_E^{\frac{\rho^2}{\rho-1}} p_E^{-\frac{\rho}{\rho-1}} + A_E^\rho]^{-\frac{1}{\rho}}.$$

Since our treatment affects both energy productivity (A_E) and energy unit cost (i.e., price) that the firm faces (p_E), we can derive how energy demand respond to an increase in energy productivity and a decrease in energy price using the log-linearization ($\widehat{A_E} < 0$ and $\widehat{p_E} > 0$), where $\widehat{A_E}$ and $\widehat{p_E}$ denote percentage changes in A_E and p_E, respectively.

We show that the change in energy demand depends on the relative effects of price/energy efficiency treatment and elasticity of substitution between energy and other inputs.

$$\widehat{E} = \underbrace{\hat{Q}}_{>0} + \underbrace{(-\frac{\theta}{\rho-1} - 1)}_{>0, or <0} \widehat{A_E(M)} + \theta \underbrace{\frac{1}{\rho-1}}_{<0} \widehat{p_E(M)},$$

where $\theta = \frac{C}{C+1} \in (0,1)$ and $C = A_X^{\frac{\rho}{\rho-1}} A_E^{\frac{-\rho}{\rho-1}} p_E^{\frac{-\rho}{\rho-1}} > 0$.

Therefore, our treatment has an ambiguous effect on firms' energy demand. The effect has to be evaluated empirically.

A2. Additional tables and figures

Source: Wikipedia (Jinan)

Figure A1: Location of Jinan city in China.

Table A1: Firm energy management questionnaire.

Practice	**Examples of questions we asked**	**Scoring criteria (points)**
Energy Management System	Whether the company has an operational energy management system a) Is there an energy management system in your company? b) Has your company met any energy management standards? If so, which standards?	**1** There is no energy management system. **3** There is an energy management system, but the relevance to any national or international energy management standards is unclear. **5** There is an energy management system, and it meets a national or international energy management standard.
Energy Management Capacity	Whether energy managers have professional energy management skills and influence company decisions a) Is there anyone formally appointed as the person in charge of energy? b) Has the person in charge of energy acquired any technical credentials or received any energy management training? c) How does the energy management team influence the company's decision making?	**1** There is no specialized energy management team. **3** There is a specialized energy management team, but only one person with limited influence on the company's decisions making. **5** The energy management team is well trained and can influence the company's decisions.
Energy Management responsibilities	Whether energy managers have well-defined formal responsibilities a) Please give a brief introduction to the organization and responsibilities to the energy management team. b) Could you specify the document that defines the above organization and responsibilities, if any?	**1** The energy management team does not have any clearly defined roles. **3** The energy management team has some responsibilities but they are not clearly defined in a formal document. **5** The energy management team and personnel have formally defined responsibilities.
Energy Laws and Regulations	Whether employees understand and conform to energy-saving laws and regulations a) Please briefly introduce how the company tracks energy-saving laws and regulations. b) Please briefly introduce the company's practices to implement these laws and regulations.	**1** The company does not track energy laws and regulations. **3** The company systematically tracks energy laws and regulations, but the company does not provide the reason for tracking or implementation. **5** The company systematically tracks the energy laws and regulations. Goals to implement them are clear, and aligned with the company's goal.
Energy Monitoring and Review	Whether the company tracks and reviews its energy use a) How often does the company measure and review its energy use? Is there a standardized process? b) Is the firm's energy use compared to any benchmarks? c) Does the company keep a comprehensive record of its energy use and review it regularly?	**1** The company does not regularly review energy use. **3** The company reviews energy use, but it does not have a clear goal and lacks consistent and quantitative measures of progress. **5** The review has a clear goal. It is conducted regularly and includes quantitative measures of progress.
Energy Benchmarking	Whether the company has a clear benchmark for measuring energy-saving progress a) What standard or approach is applied in to construct benchmark energy use, if any? b) Does the benchmark include energy use at factory, workshop, and equipment level? c) How does the benchmark treat parameters that reflect energy efficiency? d) Under what conditions are the baseline and parameters adjusted? Have they ever been adjusted in the past?	**1** The company does not set an energy benchmark to evaluate progress. **3** The company has established its benchmark energy use. There is no mechanism for regular adjustment. **5** The company has an advance energy baseline system. There is a mechanism for regular adjustment.
Energy Targets	Does the firm have energy-saving targets and how are they implemented? a) Are the firm's energy targets documented? b) Is the energy target defined at the level of the company, workshop and equipment? c) Is the company's internal target connected with any external targets or standards? d) What is the process for setting, reviewing, and adjusting energy targets? What happens if the target it met? What happens if the target is not met?	**1** There is no document describing the firm's energy targets. **3** There is a document that describes the firm's energy targets, but it is not integrated with mandatory requirements and carries no punishment for non-compliance. **5** Energy targets are well documented, aligned with regulatory requirements, and non-compliance punishments are clearly stipulated.
Information Exchange	How strong is the firm's internal communication around energy-saving goals and requirements? a) How is information on the performance of energy-using equipment exchanged among employees? b) Do employees commonly offer advice or share information on how to improve energy efficiency? Are they rewarded?	**1** Energy-saving knowledge is limited to a small group of employees and not widely understood. **3** Energy-saving knowledge is exchanged internally. Employees occasionally share advice on how to improve energy efficiency. **5** Energy-saving knowledge is frequently shared. Employees are encouraged to share advice on improving energy efficiency.
Investment and Procurement	Is energy saving considered in investment, product design, and procurement? a) Is energy saving considered in feasibility studies for new investments or products? Is an energy audit or other measures of energy use required for fixed asset investment projects? b) How does the company analyze energy use and consumption when procuring large energy intensive equipment? Do you calculate life-cycle economic costs? How long is the life cycle or depreciation period considered? c) Please describe how you track and assess energy efficiency during equipment operation and maintenance.	**1** Energy saving is not considered in investment and procurement. **3** The company considers energy saving in investment and procurement but lacks a systematic assessment approach. **5** The company considers energy saving in investment and procurement and adopts a systematic assessment approach.
Energy Management Evaluation	How does the company review and improve its internal energy management capabilities? a) How often does the company review its energy management system? What is the objective? Is the board involved? b) How do you correct any problems identified? c) How is performance reviewed? What happens if performance is not satisfactory?	**1** There is no review process, with no rewards or punishments for performance. **3** There is a review process, but the rewards and punishments are limited or not well defined. **5** There is a clear review process, and clearly defined rewards and punishments.

Table A2: Example of recommendations for one firm.

Recommendation category	**Target equipment and recommendation details**	**Estimated energy saving**
Rescheduling	a) Adjust the operation schedule of key energy-using equipment, including air compressor and shot blasting machine, to improve energy efficiency. b) Schedule more production activities to non-peak hours.	Above 30 thousand yuan per year
Transformer	a) Regularly collect key parameters, e.g., maximum load, time of use, and power factor, to monitor the unit cost of electricity. b) Adjust the maximum load demand when the production activity is low during the off-season c) Switch to a transformer with smaller capacity to improve its utilization rate and efficiency.	60 to 150 thousand yuan per year
Air compressor	a) Dynamically adjust the power output of air compressors according to production load. b) Reduce no-load period to avoid wasting energy.	About 120 thousand yuan per year
Furnace	a) The insulation of the vertical pit furnace needs to be improved. b) The batch for heating could be increased to fully use the heating capacity.	Hard to estimate due to lack of equipment-level energy use data, about 15% energy saving per unit product.
Other equipment	The flame cutting machine is suggested to be replaced by an oxyhydrogen cutting machine to improve the safety and energy efficiency.	Hard to estimate due to lack of equipment-level energy use data, about 30% energy saving per unit product.

Notes. Lighting recommendation was not provided as this firm had already adopted energy-efficient lighting before our visit.

Table A3: Treatment effects on the electricity unit cost and use (quantity) with data through 2020

	(1) **Log(unit cost)** **(yuan/kWh)**	**(2)** **Log(quantity)** **(kWh)**
Treatment * After treatment	-0.08^{+}	0.08
	(0.04)	(0.16)
Month fixed effects	Yes	Yes
Firm fixed effects	Yes	Yes
Firms	43	43
Observations	4,115	4,115
R^2	0.41	0.87

Notes. Specifications of column (1) and (2) are identical to column (1) and (2) in Table 3, with data extended to the end of 2020. Standard errors are clustered at the firm level and reported in parentheses below coefficients.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{+}p < 0.1$.

Table A4: Correlation between management scores and pre-treatment recommendation adoption for the treatment sample (24 firms) and treatment plus control sample (42 firms)

	(1) **Pre-treatment adoption (24 firms)**	**(2)** **Pre-treatment adoption (42 firms)**
Management z-score	0.00	0.01
	(0.04)	(0.03)
Log(revenue)	-0.05	-0.03
	(0.03)	(0.03)
State ownership control	Yes	Yes
Firm age control	Yes	Yes
Recommendation category control	Yes	Yes
Firms	24	42
Observations	108	189
R^2	0.35	0.45

Notes. The regression uses the same specification as equation 5 except that the dependent variable is pre-treatment adoption, and the sample includes all of the recommendations that are applicable for the firm (either adopted before the treatment or not). Column (1) uses the sample that contains all the applicable recommendations for 24 treated firms. Column (2) uses the sample that contains applicable recommendations for 24 treated firms, plus 18 control firms from the endline survey.

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{+}p < 0.1$.

Table A5: Correlation between management sub-scores and recommendation adoption

	(1) **Adoption**	**(2)** **Adoption**	**(3)** **Adoption**	**(4)** **Adoption**
Mgmt z-score (Operations)	0.07			
	(0.08)			
Mgmt z-score (Monitoring)		0.23^{***}		
		(0.07)		
Mgmt z-score (Targets)			0.20^{***}	
			(0.06)	
Mgmt z-score (Incentives)				0.18^{**}
				(0.09)
Log(revenue)	0.11^{+}	0.02	0.03	0.06
	(0.06)	(0.07)	(0.06)	(0.07)
State ownership control	Yes	Yes	Yes	Yes
Firm age control	Yes	Yes	Yes	Yes
Recommendation category control	Yes	Yes	Yes	Yes
Firms	24	24	24	24
Observations	85	85	85	85
R^2	0.21	0.34	0.30	0.26

Notes. The regression uses the same specification as equation 5 to explore the correlation between management sub-scores and adoption. Standard errors are clustered at the firm level and reported in parentheses below coefficients.

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{+}p < 0.1$.

Table A6: Correlation between management and pre-treatment electricity unit cost or use (quantity) for full sample (91 firms, monthly data from 2013 to 2015)

	(1) Log(unit cost) (yuan/kWh)	**(2) Log(quantity) (kWh)**
Management z-score	-0.07***	-0.17
	(0.02)	(0.14)
Log(revenue)	0.03^{+}	0.87***
	(0.02)	(0.10)
State ownership control	Yes	Yes
Firm age control	Yes	Yes
Year control	Yes	Yes
Firms	91	91
Observations	3217	3217
R^2	0.07	0.58

Notes. The table reports the correlation between management score and pre-treatment electricity unit cost or quantity using equation 6 with the full sample collected in the baseline survey. Standard errors are clustered at the firm level and reported in parentheses below coefficients.

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{+}p < 0.1$.

Table A7: Shandong electricity price schedule for large industrial users.

Voltage level (VL)	**Price per kWh**					**Monthly fixed cost based on transformer capacity or maximum load (yuan/kVA)**
	Benchmark price (yuan/kWh)	Time-of-use pricing multiplier				
		Summit hours	Peak hours	Base hours	Valley hours	
1 kV $\leq VL \leq$ 10 kV	0.6646	1.7	1.5	1	0.5	28 or 38
35 kV $\leq VL <$ 110 kV	0.6496	1.7	1.5	1	0.5	28 or 38

Sources. Shandong Bureau of Commodity Price (April 2015).
Notes. The benchmark price is occasionally changed by the Shandong Bureau of Commodity Prices, and changes apply uniformly to the population of firms. Summit hours (10:30–11:30, 19:00–21:00 from June to August), peak hours (8:30–11:30, 16:00–21:00 from September to May; 8:30–10:30, 16:00–19:00 from June to August), base hours (11:30–16:00, 21:00–23:00, 7:00–8:30), and valley hours (23:00–7:00).

Table A8: Correlation between management and electricity unit cost or use (quantity) in 2019 and 2020.

	(1) Log(unit cost) (yuan/kWh)	(2) Log(quantity) (kWh)
Management z-score	0.02	-0.07
	(0.03)	(0.21)
Treatment	-0.10^{+}	0.05
	(0.05)	(0.40)
Log(revenue)	-0.02	0.79***
	(0.02)	(0.19)
State ownership control	Yes	Yes
Firm age control	Yes	Yes
Month control	Yes	Yes
Firms	43	43
Observations	1,029	1,029
R^2	0.12	0.36

Notes. The table reports the correlation between management score and post-treatment electricity unit cost or quantity using equation 6 with data for 2019 and 2020. Standard errors are clustered at the firm level and reported in parentheses below coefficients.

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{+}p < 0.1$.

Table A9: Treatment effects on the electricity unit cost and interactions with management sub-scores.

	(1) Log(unit cost)	(2) Log(unit cost)	(3) Log(unit cost)	(4) Log(unit cost)
Treatment * After treatment	-0.09**	-0.07^{+}	-0.08**	-0.08**
	(0.04)	(0.04)	(0.04)	(0.04)
Treatment * After treatment * Mgmt z-score (Operations)	0.02			
	(0.02)			
Treatment * After treatment * Mgmt z-score (Monitoring)		0.06**		
		(0.03)		
Treatment * After treatment * Mgmt z-score (Targets)			0.04^{+}	
			(0.02)	
Treatment * After treatment * Mgmt z-score (Incentives)				0.05^{+}
				(0.03)
Month fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Firms	43	43	43	43
Observations	3,602	3,602	3,602	3,602
R^2	0.44	0.45	0.45	0.45

Notes. The table reports the results on the treatment effects interacted with management sub-scores using equation 7. Standard errors are clustered at the firm level and reported in parentheses below coefficients.

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{+}p < 0.1$.

Table A10: Correlation between management sub-scores and pre-treatment electricity unit cost and use for the experiment sample (48 firms, monthly results from 2013 to 2015)

	Log(unit cost) (yuan/kWh)				**Log(quantity) (kWh)**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Treatment	-0.01	-0.02	-0.01	-0.02	0.06	0.04	0.05	0.02
	(0.06)	(0.05)	(0.05)	(0.05)	(0.27)	(0.26)	(0.26)	(0.26)
Log(revenue)	0.01	0.03	0.03	0.03	0.75***	0.73***	0.76***	0.81***
	(0.03)	(0.02)	(0.03)	(0.03)	(0.14)	(0.14)	(0.15)	(0.13)
Mgmt z-score (Operations)	-0.03				-0.07			
	(0.03)				(0.17)			
Mgmt z-score (Monitoring)		-0.08***				0.00		
		(0.03)				(0.14)		
Mgmt z-score (Targets)			-0.06**				-0.08	
			(0.03)				(0.15)	
Mgmt z-score (Incentives)				-0.07***				-0.22
				(0.02)				(0.15)
Firms	48	48	48	48	48	48	48	48
Observations	1,718	1,718	1,718	1,718	1,718	1,718	1,718	1,718
R^2	0.04	0.13	0.07	0.08	0.53	0.53	0.53	0.55

Notes. The table reports the correlation between management sub-scores and pre-treatment electricity unit cost or quantity using equation 6. Standard errors are clustered at the firm level and reported in parentheses below coefficients.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{+}p < 0.1$.

Table A11: Correlation coefficients between management and energy management practices from the baseline survey.

Variables	**Management z-score**	**Energy management z-score**	**Energy management: Standard**	**Energy management: Team**	**Energy management: Target**
Management z-score	1.00				
Energy management z-score	0.53	1.00			
Energy management: Standard	0.42	0.70	1.00		
Energy management: Team	0.43	0.74	0.62	1.00	
Energy management: Target	0.35	0.59	0.44	0.53	1.00

Notes. $N = 91$. All the correlations are statistically significant at the 1% level.

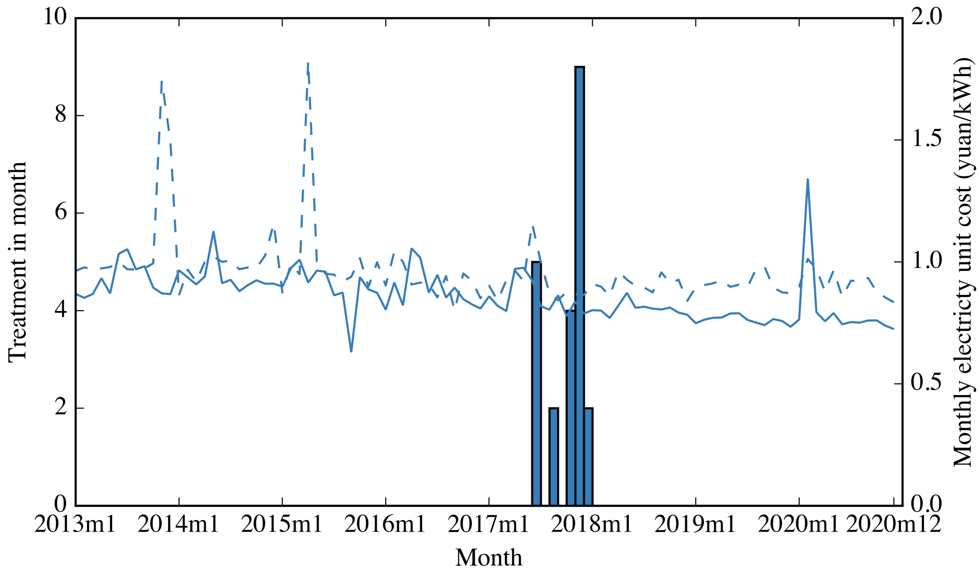
(a) A metal press in one of the plants in our sample.

(b) Metal raw materials outside one of the plants in our sample.

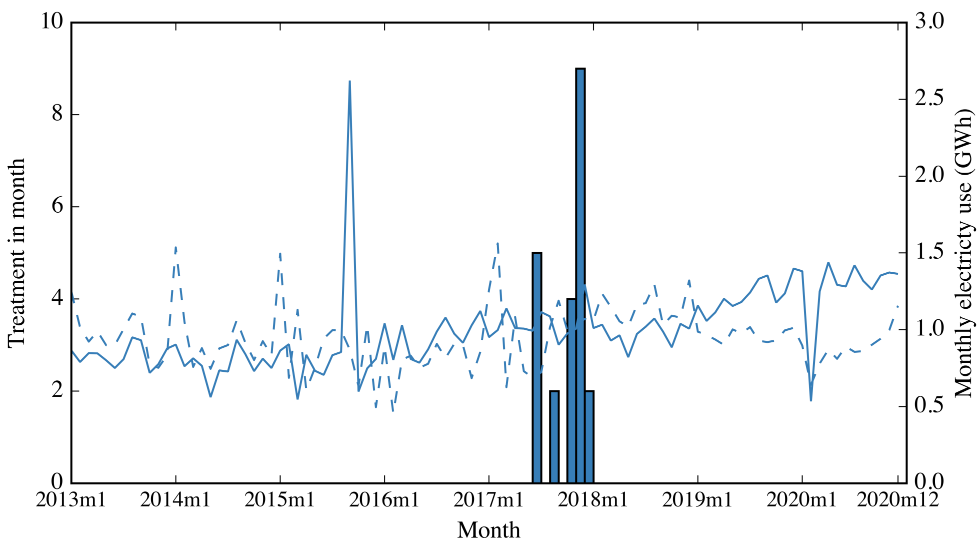
(c) Women working on metal lathes in one of the plants in our sample.

(d) Plant workers heading to lunch at one of the plants in our sample.

Figure A2: Photographs of the physical setting and production floor at several firms in our sample.



(a)



(b)

Figure A3: Treatment timing and trends of revenue-weighted average (a) electricity unit cost and (b) electricity use. Solid line – treated firms; dashed line – control firms.

Notes. Bar charts show the frequency of treatment initiation by month.

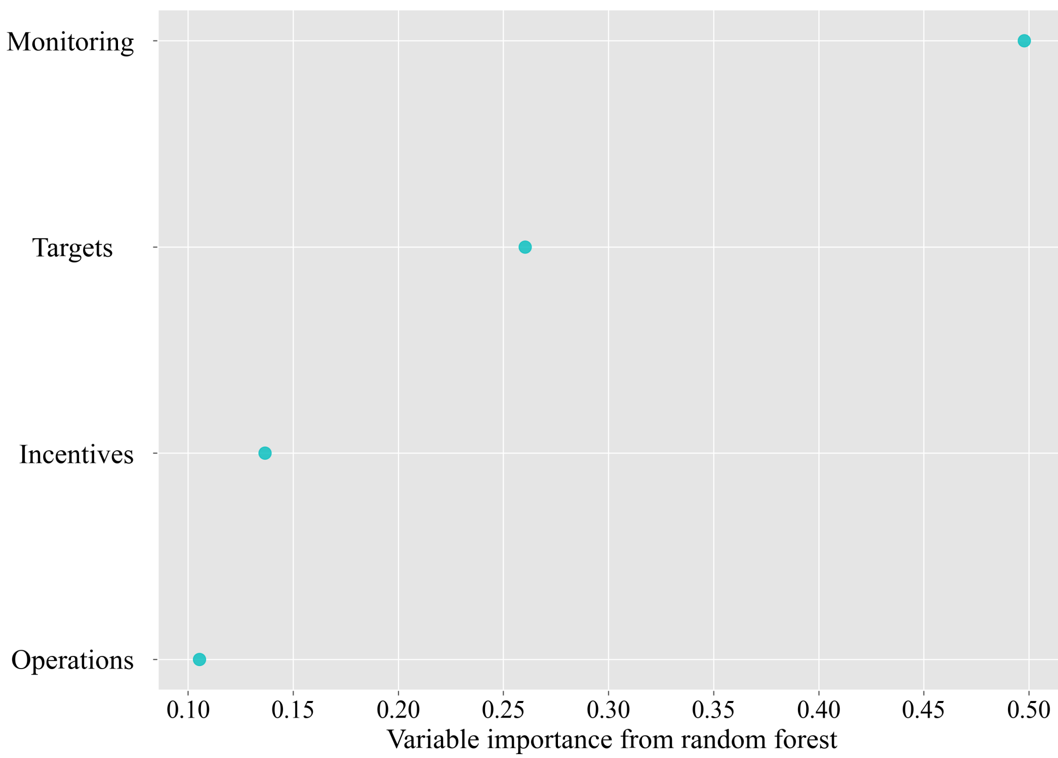


Figure A4: Correlation between management sub-scores and recommendation adoption.

Notes. The figure shows random forest estimates of variable importance using the same sample as Appendix Table A5. Variable importance is estimated following the process described in [11].

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