# Does Renewable Energy Renew the Endeavor in Energy Efficiency?

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Improvement in energy efficiency (EE) has slowed globally since 2015 and is now falling short of the 2.6% per year target recommended by the United Nations Sustainable Development Goals, despite an abundance of EE opportunities. Barriers to EE have existed long before the rise in renewable energy (RE) investment. However, increased RE adoption may have unintended consequences for improving EE as adoption may raise or lower the barriers to EE. In this paper, we examine *whether* and *how* RE adoption can increase or decrease EE improvement. On the one hand, RE represent a competitor to EE for managerial attention and budget. On the other, the adoption of RE may increase the overall awareness of energy usage and drive EE improvement. Using site-level data from an industrial conglomerate, we estimate the impact of changes in RE usage and in the acquisition approach on the EE of 183 sites across the globe from 2015 to 2020. On average, we find that using RE to meet 10% more of a site's energy demand led to an additional 2.0% improvement in EE. However, there is significant heterogeneity in the effects depending on the acquisition approach. We find that while purchasing RE credits or entering into power purchase agreements led to gains in EE, installing on-site RE generators had no effect. To understand these gains, we surveyed site managers regarding their attitudes and intentions. The results suggest that there was a greater focus on EE by both managers and workers after increasing their RE usage. We also find quantitative evidence of managers submitting more budget requests for EE improvements in the twelve months following increases in RE. For corporations looking to use more RE, we offer evidence of additional returns in the form of energy savings, but realizing them requires careful consideration of the acquisition approach of RE.

*Key words: Energy efficiency, renewable energy, power purchase agreement, on-site energy generation*

## 1. Introduction

The Sustainable Development Goals of the United Nations, established in 2015, call for doubling the historical rate[1] of improvement in *energy efficiency* (EE), which translates to a target of reducing global *energy intensity* (measured by the ratio of total energy consumption to GDP) by 2.6% annually until 2030 (United Nations 2021). This target was briefly achieved in 2015 with a 2.9% reduction in energy intensity, but the reduction has slowed in recent years. In 2018, global energy intensity declined by only 1.1% (IEA et al. 2021), which was the smallest decline since 2011 and continued a trend of diminishing improvement since 2015.[2] Similar patterns have been observed in the U.S., where energy intensity has been declining at a slower rate in recent years, and the next 30 years are projected to bring about only a 1.3% annual reduction (EIA 2021a). Furthermore, there is significant variation across sectors, with energy intensity of the industrial sector projected to decline by just 11% from 2019 to 2050 (EIA 2020).

While energy intensity varies with the composition of economic activities, improving *technical EE*—reducing energy usage of a given activity, such as producing one unit of product—is a key driver of overall EE improvement. IEA (2019) finds that improvement in technical EE has gradually declined since 2015 and is "*a major reason for the slowdown in energy intensity improvement and reflects limited progress on policy and investment.*" Despite slowing improvement, technical EE opportunities remain abundant (Muthulingam et al. 2013, Goldstein 2020, Dhanorkar and Siemsen 2021, IEA 2021). Opportunities range from major system upgrades (e.g., HVAC and steam systems) to less capital-intense projects (e.g., LED lighting, programmable thermostats, occupancy sensors) to no-cost initiatives (e.g., reducing machine standby and other behavioral changes of employees). Barriers to improving EE have been examined extensively in the literature (see Section 2), and they generally fall into three categories: economic/financial, regulatory, and informational barriers (DOE 2015).

These barriers have existed long before modern renewable energy (RE) gained traction, e.g., installing on-site solar power systems and purchasing RE from independent power producers. The rise in RE adoption may nevertheless have unintended consequences for improving EE, as RE investments may raise or lower the barriers to EE. Financially, investments in RE may compete for capital with EE projects. Behaviorally, consuming RE may increase the overall awareness of the importance of energy sustainability, thus increasing EE improvements. At the same time, knowing that certain RE sources, such as solar, has zero marginal cost may create perverse incentives for consuming more energy, akin to the solar rebound effect (Deng and Newton 2017). Thus, it is unclear, *a priori*,

[1] Based on the average rate from 1990 to 2010.

[2] The energy intensity declined by 2.9% in 2015, by 2.4% in 2016, by 1.8% in 2017, by 1.1% in 2018, by 2.0% (preliminary) in 2019, and by 0.8% (preliminary) in 2020 (IEA et al. 2021).

whether embracing RE may have a positive or negative impact on EE.

In this paper, we study *whether* and *how* RE adoption can increase or decrease EE improvement. While there is prior work on the relationship between RE and EE (see detailed review in Section 2), it has largely been cross-sectional and focused at the household (Dato 2018) or the macroeconomic level (Ollier et al. 2020). The former is based on household survey data that does not capture investment decisions, and the latter uses variations across countries to estimate the relationship, which is too broad to yield actionable insight. In contrast, we leverage a unique site-level dataset from a global industrial conglomerate spanning 2015–2020 that contains detailed information about site-specific RE investments, their types (e.g., on-site generation or purchase from third-parties), amount of RE generation, total energy consumption, and total industrial production. Our data enables us to undertake more granular analysis that delves into differences across factory sites and provides specific managerial recommendations.

We estimate a fixed-effects model to examine whether a shift towards using more RE leads to an improvement in EE. Across 183 manufacturing sites, we find that using RE to meet 10% more of a site's energy demand led to an average of additional 2.0% improvement in EE at that site. Annually, this represents over three-quarters of the 2.6% improvement target set forth by the United Nations.

On aggregate, this appears to be a major unaccounted gain from increasing RE adoption; however, there is significant heterogeneity in outcomes depending on the RE acquisition approach. An industrial site can acquire RE directly from on-site generation (e.g., install solar panels) or indirectly from third-parties via contracts. Different approaches imply not only different gross capital expenditures, but also different timings of those expenditures—installation of on-site generation involves a one-time payment with minimal ongoing costs while power purchase contracts require ongoing payments. We leverage the heterogeneity in the approaches to RE acquisition across our sites in order to examine how direct generation and indirect sourcing may differ in their effects on EE. We find that while indirect sourcing of RE increased EE improvement, direct generation had either no effect or may actually have led to losses in EE.

To understand the mechanisms behind the gains and the heterogeneous effects, we conducted interviews with four site managers and administered a survey to all site managers across the company. Site managers reported a change in their attitude and their workers' attitudes towards EE after changes in energy sourcing. Furthermore, we delved into capital allocation requests made by site managers after a corporate program was put in place to fund site improvements in 2016. For every 10% increase in the share of energy from RE, we find an overall 2.4% increase in the number of total allocation requests for EE improvements made by managers in the following 12 months.

Our findings are particularly important for all stakeholders as the pace of RE sourcing accelerates while EE improvements slows down. Corporations have shown a growing interest in RE: 94 of the Fortune 500 companies have set goals to buy or invest in RE, up from 53 that had set goals in 2017 (World Wildlife Fund 2021). Among the 94 companies, 58 have set 100% RE targets (including the targets to procure all electricity from renewable sources and the targets to meet all energy needs using renewable sources). And of these 58 companies, 44 are members of RE100, a global initiative that is driving the transition toward 100% renewable electricity. While corporations typically have flexibility in choosing how they would like to achieve their RE targets, current practices do not consider (or understand) the potential side effects of RE sourcing on EE. Our research provides insight for corporations and policy makers to understand whether the increasing penetration of RE could renew the endeavor in EE, and which approach(es) to RE sourcing creates the strongest synergies with EE.

## 2. Literature Review

Our paper is related to several streams of research including RE sourcing, EE, and their interaction. It is also related to work on lean operations and sustainable manufacturing, as well as corporate sustainability initiatives and market responses. We review each of these areas in detail below and discuss them in the context of our study.

### 2.1 RE Sourcing and EE

Over 300 companies worldwide have joined the global corporate RE initiative known as RE100, which requires member companies to achieve 100% renewable electricity usage by 2050, with specific interim targets (`www.there100.org`). This has led to increased adoption of RE and capacity utilization, which has accelerated the retirement of coal power plants (Drake and York 2021). It has put a spotlight on figuring out how to and how much RE to source. Agrawal and Yücel (2021) describe and compare four ways that corporations can source RE: purchase unbundled RE certificates (RECs), participate in utilities' green pricing or green tariff programs, enter into power purchase agreement (PPAs), or install RE generation projects. Guajardo (2018) compares the solar system performance under corporate ownership and third-party ownership, and finds that the third-party owned systems have a higher capacity factor than self-owned systems. Trivella et al. (2021) study how companies meet their renewable power targets using a dynamic portfolio of PPAs; shortfalls from the target are met by purchasing unbundled RECs. Our work contributes to the sourcing discussion by highlighting heterogeneity in operational outcomes that are predicated on RE sourcing.

RE sourcing is an important component, but EE makes up the other leg of the sustainable development goals. EE, which aims to use less energy to produce the same output, encompasses not only process/technological upgrades, but also energy consumption behavior. While it is well known that EE upgrades are abundant and many have short payback periods, the reality is that many opportunities are not adopted—a phenomenon known as the "energy efficiency paradox" (Gerarden et al. 2017). Explanations for the energy paradox have been well studied by Hirst and Brown (1990), DeCanio (1993), Jaffe and Stavins (1994), Gillingham et al. (2009), and Gerarden et al. (2017). They include principal-agent problems, capital constraints, uncertainty about actual savings, bounded rationality, perceived quality of EE products, lack of management attention, and lack of credible information about returns on investments. There have also been a number of proposed solutions for resolving the paradox (DeCanio 1993, Sandberg and Söderström 2003, Muthulingam et al. 2013, Aflaki et al. 2013). Our work touches on several of these frictions, specifically principal-agent problems (i.e., employees do not pay energy bills), capital constraints, and lack of management attention in a real world context.

While the investment in and execution of efficiency projects are important in bringing about process and technological upgrades, there are also important levers to consider for changing consumption behavior. Nguyen et al. (2018) analyze how EE assessment assistance and buyers' procurement commitment can incentivize suppliers' EE investment. Dhanorkar and Siemsen (2021) find that nudges in the form of reminders can serve as a managerial lever to focus attention on discretionary tasks such as implementing EE projects, especially under a higher number of parallel EE and non-EE tasks (e.g., project on water, waste, or pollution).

Changes in EE and RE technologies are fundamentally reshaping electricity demand patterns and supply portfolios. Not surprisingly, these two types of initiatives have been discussed together, and their interactions have been studied. While synergies were not found in certain policy settings (Ollier et al. 2020), there may still be advantages to corporations (Prindle et al. 2007). Households may similarly face conflicting effects depending on the setting (Dato 2018). IRENA (2017), IRENA and C2E2 (2017) point out that for a given amount of RE, greater EE results in higher shares of RE. Coenen et al. (2017) and Hoppe et al. (2019) discuss how RE supplying cooperatives (REScoops) allow their members to collectively own RE facilities and consume RE. Evidence suggests that REScoops can use their specific position as energy suppliers to stimulate their members to save energy.

We build upon this stream by studying how RE sourcing affects EE in an industrial setting. Our work looks at how careful sourcing decisions could be a solution for overcoming barriers to EE from both a technological and behavioral standpoint. Our research strikes a similar chord to the literature, but from a different angle: organizations that adopt more RE, especially via ongoing contractual payments, might have increased the management attention on sustainable energy, leading to more energy-saving behavior and investment in EE technologies.

### 2.2 Lean and Sustainable Manufacturing

Procuring RE can be considered from the perspective of "going green" (the facilities we study generally have to pay premiums for RE), while improving EE can be considered as "going lean."

Porter and Van der Linde (1995) and Hart (1997) lead the idea that pollution prevention and cleaner technology yield important competitive benefits. King and Lenox (2002) argue that managers underestimate the benefit of solving waste problems at their source. Corbett and Klassen (2006) find that many benefits of adopting an environmental perspective were unexpected. They refer to these benefits as the expected unexpected side benefits, given that they seem to recur frequently. In this paper, we explore whether the costly green effort (procuring RE) can have unexpected benefits, such as encouraging EE improvements.

The relationship between lean and green has been studied extensively. Florida (1996) argues that efforts to improve manufacturing processes and increase productivity create incentives for adoption of environmentally conscious manufacturing strategies. In other words, lean embraces green because some green strategies are inherently lean. The author also notes that the closer a firm gets to zero emissions the more expensive it becomes to further reduce pollution. King and Lenox (2001) analyze 17,499 U.S. manufacturing establishments and find that adoption of the quality standard ISO 9000 increases the likelihood of adopting adopting the environmental management standard ISO 14000, which supports the argument that adoption of lean production may lower the marginal cost of pollution reduction. They also show that lean production is associated with lower emission, which supports the assertion that "lean is green." King and Lenox (2002) analyze 614 publicly traded U.S. manufacturing firms and find that waste prevention (not waste treatment) leads to financial gains, which supports the argument that "it pays to be green." Corbett and Klassen (2006) point out that once the boundary of a traditional field is expanded to include environmental perspective, the benefits tend to recur but are unpredictable, which may explain why the environmental benefits are often underestimated.

### 2.3 Market Responses to Corporate Sustainability Initiatives

Finally, our paper is related to the research on the corporate sustainability movement. Many large corporations have established sustainability targets and started numerous initiatives to achieve these targets. Dowell et al. (2000) find that multinational enterprises adopting stringent global environmental standards have higher market values than firms defaulting to less stringent or poorly enforced host country standards. However, the positive reaction of the market to the sustainability effort is not universal, because effort can be costly. Jacobs et al. (2010) find that ISO 14001 certifications and philanthropic gifts for environmental causes are associated with significant positive market reaction, whereas voluntary emission reductions are associated with significant negative market reaction—the latter is also supported by the findings in Fisher-Vanden and Thorburn (2011) and Alsaifi et al. (2020). Despite these mixed market reactions, it is clear that investors care about climate risks. Recent surveys of institutional investors conducted by Krueger et al. (2020) show that they generally think that climate risks matter financially. To address climate risks, the institutional investors consider engagement of the portfolio firms, rather than divestment of them. Engagement can range from private discussions with management to public actions (e.g., criticisms). Ramelli et al. (2021) find that although the 2016 U.S. election boosted the stock prices of carbon-intensive firms, firms with climate-responsible strategies also gained, especially those firms held by long-run investors. This result implies a significant number of investors value firms' climate-responsible strategies as preparation for a more climate-conscious economy.

The positive market responses to corporate sustainability initiatives calls for more effective ways to implement the initiatives and achieve the set targets. Energy-related sustainability targets can be achieved through EE initiatives and RE adoption. Kleindorfer et al. (2005) describe that the internal strategies for the future include investing in capabilities to develop substitutes for nonrenewable inputs and to redesign products to reduce their material content and their energy consumption during manufacturing and use (i.e., EE). To the best of our knowledge, our paper is the first to build on this by examining another potential benefit of RE adoption—that of improved EE.

## 3. Hypotheses Development

There are various plausible reasons why the recent RE adoption may negatively affect the enduring effort in EE. One of the key barriers to EE in an industrial facility is the internal competition for capital. DOE (2015) considers internal competition for capital as a top barrier to investing in EE. Direct generation generally requires a large upfront investment. For example, rooftop solar for industrial facilities costs \$1.72/W of generation capacity on average in 2020 (NREL 2021). Thus, a facility needing 200 kW of solar power on average needs to install a 1.2 MW solar power system[3]—a sizable investment of about \$2 million, despite costs dropping significantly (costs of solar were \$5.57/W in 2010). Such a capital-intensive project certainty competes for capital with EE improvement projects. In the case of PPAs with third-parties, contractual prices are typically higher than the average price of electricity from utilities partly because the RECs are factored into PPA prices as well.

[3]Capacity factor for rooftop solar is typically around 16 to 20%.

Aside from tightened capital budgets, RE projects also divert management attention away from EE opportunities. Attention may be diverted by a variety of factors, among which is the tendency for RE projects to receive more favorable press reports than improvements in EE. Furthermore, much of the low-hanging fruit in EE involves behavioral changes that require constant management attention. In contrast, RE projects are technical changes that require one-time attention.

On the other hand, one of the well-known informational barriers to EE is the lack awareness of the benefits, incentives, and programs. Efforts to increase awareness has focused on nudging industrial decision-makers (Dhanorkar and Siemsen 2021) over the past three decades. Research has shown that decision-makers do need reminders or nudges to take on EE opportunities and that RE and EE can be complements (see Section 2.1). Embracing RE at industrial facilities could increase the overall awareness of the facilities' overall "energy health." Therefore, it is conceivable that engaging in RE sourcing might serve as a *de facto* "nudge" for improving EE. This "nudge" by RE is present and visible daily for those managers and can act as a consistent reminder for the need to improve EE. For managers who are good at fostering behavioral changes, RE adoption might become an opportunity to reinforce or even boost the behavioral changes for greater gains in EE.

Many of the above potential effects of RE adoption on EE may co-exist; thus, the overall effect is unclear. We therefore formulate the following competing hypotheses:

**Hypothesis 1a** *Using more RE decreases EE.*

**Hypothesis 1b** *Using more RE increases EE.*

Hypothesis 1 focuses on the overall effect of RE adoption on EE, but there may be heterogeneous effects depending on how industrial facilities adopt RE. There are multiple pathways that facilities can employ. They can acquire RE i) directly from on-site generation; ii) indirectly from third-parties via PPAs; or iii) by simply purchasing unbundled RECs. These different approaches of procuring RE may act differently on the barriers to EE.

When a facility chooses to deploy on-site generation, such as installing a solar power system, it makes an upfront investment and then enjoys on-site energy at almost zero marginal cost (maintenance cost is nominal for solar panels). While intuitively the upfront investment tends to divert capital away from EE improvements, this discouraging effect may go beyond budget competition. Note that the investment is sunk regardless of whether the facility is paying the installation cost all at once or over time. With the sunk investment bringing "free" energy over many years to come, managers may attend less to EE, and in turn reduce employee motivation to save energy. For instance, evidence from our factory visits showed many instances of energy being wasted. In one case, a machine was left on (and not producing products) during a lunch break. When the operator was asked about the energy waste, their answer was "*It's free energy because of the solar panels; it's all going to get wasted if we don't use it.*" While the quote was surprising to the research team, the response was understandable given the incentives. Research in the residential sector has found that solar consumer may consume more electricity than before installing solar—a solar rebound effect. Deng and Newton (2017) find that this rebound effect erodes up to 21% of the benefit of solar energy for some households. Qiu et al. (2019) estimates that for every 1 kWh increase in solar electricity generation, solar homes increase their total electricity consumption by 0.18 kWh.

On the other hand, on-site generation is physically visible and therefore may be more effective in increasing the awareness of energy sustainability among managers and employees. Sánchez-Pantoja et al. (2018) surveyed participants on their emotional response to photographs of buildings and photovoltaic systems and found that integrated photovoltaic systems were rated as more pleasant than mounted solar systems. Spielhofer et al. (2021) conducted a lab experiment and found that participants were significantly more physiologically aroused while viewing landscapes with more RE systems. Also using lab experiments, Carlson et al. (2020) found that emotionally positive images of climate change solutions (e.g., windmills and solar panels) capture attention, whereas emotionally negative images do not. They also found that a person's motivation to protect nature is associated with attention allocation to environmentally relevant stimuli. In our context, on-site RE generation may increase managers' and employees' attention allocation to pro-environmental actions, such as EE. Hence, we have the following competing hypotheses for the effect of on-site RE.

**Hypothesis 2a** *Using more on-site RE decreases EE.*

**Hypothesis 2b** *Using more on-site RE increases EE.*

When a facility chooses to purchase RE from third-parties via PPA, the facility pays for RE at a contracted price, incurring a steady flow of energy procurement cost. This cost stream typically increases energy expenses (PPA prices include RECs) and may compete for budget with EE. On the other hand, in contrast to the on-site generation, the procurement costs through PPAs are not predetermined; they vary with the output of the solar site. Facilities pay the solar power producers regularly as if they pay the utility bills. Therefore, under PPAs, conscientious purchasing of RE every month may encourage management to pay more attention to energy consumption and EE as well. This leads to the last competing hypotheses of the effect of third-party RE.

**Hypothesis 3a** *Procuring more RE from third parties decreases EE.*

**Hypothesis 3b** *Procuring more RE from third parties increases EE.*

# 4. Context and Data

## 4.1 Context

We are interested in the relationship between RE adoption and EE improvement in the industrial sector. In the U.S. in 2020, industrial energy consumption totaled 31 quadrillion British thermal units, a 33% share of all energy consumed (EIA 2021b, Table 2.1 to 2.5), which is also the highest among the four major energy end-use sectors (transportation 26%, residential 22%, commercial 18%). At the same time, the industrial sector is projected to have the smallest EE improvement among the four sectors (EIA 2020). Improving EE in the industrial sector has U.S. Congressional attention (DOE 2015) and is a key part in achieving the United Nations Sustainable Development Goals.

Besides being a significant energy end-user, the industrial sector is also interesting because of its variety of energy procurement approaches. Firms may purchase electricity from utilities as well as independent power producers. They may generate electricity themselves using purchased fuels or residuals from manufacturing processes. Firms may also invest in renewable power generators, such as solar photovoltaic systems and wind turbines. It is the amount of energy consumed, its slower rate of EE improvement, the ability to independently contract with power producers and to install on-site generation technologies—both at scale—that sets the industrial sector apart from others when analyzing consumption options and patterns. The opportunity to choose among these energy procurement approaches allows us to identify levers that may drive changes in other areas.

## 4.2 Data

Our data is drawn from a publicly-traded conglomerate in the consumer goods space. The company's products are found in almost every country and is supplied by sites that are distributed across the globe. The firm is a Fortune 200 publicly listed company with approximately 200 sites globally. Each site is independently managed by a site manager, who is responsible for all on-site operations and whose compensation is directly tied to their site's performance.

The data consists of monthly site-level data from 2015–2020. (Our data extends back to 2011, but the earlier years do not capture energy costs. In Section 7, we extend our main results to include these years subject to this data limitation.) The data covers 183 manufacturing sites that were operational throughout our study period. They are located in over 50 countries across six continents. The sites manufacture a wide array of consumer goods that are classified into 13 sub-categories, which can be rolled up into three primary product groups. These sites consumed over 120,000 GJ of electricity annually over the sample period, and the total spend over six years was approximately $2.2 billion.

The data has several distinct advantages in answering our research questions. First, our level of analysis—the site-month level—allows us to capture granular variations in our variables of interest while controlling for sources of heterogeneity. Second, we have production quantities that are centrally determined at HQ, but all operational decisions around managing the factory are made locally. The exogenously determined production quantity allows us to disentangle any simultaneity bias where quantity may be jointly determined with energy consumption to maximize the overall profit. Finally, production quantity is a cleaner measure of output than GDP used in other studies. A site's energy consumption normalized by its production quantity precisely captures the technical EE (introduced in Section 1) at that site.

As part of the company's performance measures and an outcome related to performance, the data is audited by an external third party. The audit team compares the reported numbers against the information from each site's local records, and each record is linked to a utility bill, e.g., fuel purchase invoice, power purchase payment receipt, and more. Thus, the data is both internally and externally consistent, which gives us confidence in our results.

Members of the research team work with the company on a long-term consulting project. This relationship allowed us to obtain a detailed understanding of the data and to continually follow up with corporate and site managers to better understand the implications of our findings. With the exception of not being able to name the company nor provide material information that identifies them, we were not restricted in reporting our findings.

#### 4.2.1 Independent Variables

**RE Percentage.** Our primary independent variable of interest is the share of site energy demand that is met by renewable sources. Our data breaks down the source of energy at the site level monthly. Each month, sites report on how many gallons of fuel they consumed, how much electricity/natural gas was used, how many kWh of solar energy was generated, how much energy they consume, etc. This is all reported in a standardized format so all sites globally supply the same level of information, which can all be compared.[4] On-site renewable sources include geothermal, hydro, solar, wind, and biogenic fuels. Sites can also acquire RE via renewable PPAs and RECs. The rest of the energy is from fossil fuels (coal, natural gas, fuel oils) and electric utilities.[5] For each site in each month, we aggregate consumption by RE sources and derive a measure ($RE\%$) defined as the percentage

[4] Site energy consumption from each source is independently verified and audited by a multinational third party. For energy purchases via PPAs, in order to be certified as renewable, the contracted producer must feed green power into the same grid from which the specific site draws its power. Note that this is a stricter requirement than simply purchasing RECs, which companies often use to greenify their energy usage, from a location agnostic provider (e.g., a North American airline purchasing green credits from a solar energy provider in Australia). While all power supplied to a grid are just electrons, the PPAs allow the buyer to contract for not just the energy itself, but also the energy's green attribute.

[5] Categorization is based on the U.S. Environmental Protection Agency (EPA) categorization of energy supply: https://www.epa.gov/green-power-markets/what-green-power

of total demand met by renewable sources acquired by the site. Note that utilities may have their own renewable sources, but the sites cannot claim ownership of RE from the utilities, because the utilities typically own the RECs derived from their renewable sources.

To study how RE acquisition approaches may affect EE, we segment RE consumption into three categories—direct on-site generation, PPAs, and RECs. Direct on-site generation is the energy directly generated by a site's own equipment; RE from PPAs is the demand met by energy sourcing agreements between the site and independent renewable power producers, such as a solar farm; the REC amount is the demand covered by green credits purchased by the site. We divide these three quantities by the site's total energy consumption to obtain three measures: $RE\%^{Onsite}$, $RE\%^{PPA}$, $RE\%^{REC}$, which represent the percentage of total demand that is met through each approach.

**Energy Cost.** We capture the cost of energy using the average annual cost ($\bar{Cost}$), which is calculated by taking the total cost divided by total energy and is measured in dollars per gigajoule (\$/GJ). While the granularity of our data allows us to calculate a month-level cost figure, seasonality may play a significant role in costs and generated output. For example, solar output is lower in winter months, and certain fuels like heating oil and natural gas increase in price during colder times of the year. Furthermore, managers are compensated based on their annual performance. Therefore, we include aggregated annual costs as a control to remove seasonal effects as well as to align our measures with the decision-maker's time frame. We separate costs for fossil and renewable sources and denote them as $\bar{Cost}^F$ and $\bar{Cost}^R$, respectively.

**Production.** Production ($Prod$) is measured as the total finished product weight in tons. While this is an aggregate measure that has significant heterogeneity across product lines, we account for these differences in our empirical strategy using a combination of controls and fixed effects (see Section 5). We utilize production both as an explanatory variable, as well as a normalizing factor for total energy usage.

**Other Controls.** For each site, the data also captures site characteristics including location, product category, and operating status. Location is the country where the site operates, product category groups all products into 13 categories, and operating status is a binary variable indicating whether the site was operating in that month-year observation.

#### 4.2.2 Dependent Variable

**EE.** We measure EE in each month at each site in two ways. First, we use total energy consumption (measured in GJ) as a dependent variable, abbreviated as *Energy*. Second, we normalize energy use by production, which gives energy per ton of production ($EPTOP$) given by:

$$EPTOP = \frac{\textit{Total Energy Consumption (in GJ)}}{\textit{Production (in tons)}}. \tag{1}$$

We select controls to account for product and factory-size differences. We incorporate site fixed effects so that we are only utilizing within-site variation. This controls for all time invariant heterogeneity including that of any unobservables. Intuitively, in this context, this means that we are only analyzing deviations from a site's own average energy consumption. We also include various functional transformations of $Prod$ as independent variables to allow for non-linear effects of production quantity on energy use, which captures economies or dis-economies of scale. For example, it takes roughly the same amount of energy to run the blast chillers in ice cream manufacturing regardless of how large of a batch is placed in the chiller.

### 4.3 Sample Statistics

We check for a balanced panel of all the variables of interest described above, which yields our sample of 183 sites spanning from 2015 to 2020, totaling 13,176 observations. Summary statistics are shown in Table 1. Fossil and Renewable are breakdown of total energy use into their respective source.

Table 1: Summary Statistics: Monthly Observations from 2015–2020

| Statistic | N | Mean | Stdev. | Pctl(25) | Median | Pctl(75) |
|---|---|---|---|---|---|---|
| Energy (GJ) | 13,176 | 9,162 | 9,698 | 2,607 | 6,692 | 12,047 |
| Fossil (GJ) | 13,176 | 6,155 | 8,200 | 1,086 | 3,642 | 8,098 |
| Renewable (GJ) | 13,176 | 3,007 | 4,565 | 0.00 | 1,189 | 4,369 |
| RE% | 13,176 | 0.36 | 0.35 | 0.00 | 0.32 | 0.65 |
| RE%$^{PPA}$ | 13,176 | 0.25 | 0.32 | 0.00 | 0.00 | 0.50 |
| RE%$^{REC}$ | 13,176 | 0.05 | 0.16 | 0.00 | 0.00 | 0.00 |
| RE%$^{OnSite}$ | 13,176 | 0.06 | 0.18 | 0.00 | 0.00 | 0.00 |
| Prod (tons) | 13,176 | 7,448 | 8,623 | 2,017 | 4,722 | 9,397 |
| EPTOP (GJ/ton) | 13,176 | 3.12 | 14.32 | 0.69 | 1.24 | 2.02 |
| $\bar{\text{Cost}}^F$ (\$/GJ) | 13,176 | 14.85 | 19.67 | 6.94 | 11.89 | 19.67 |
| $\bar{\text{Cost}}^R$ (\$/GJ) | 13,176 | 18.81 | 44.98 | 0.00 | 15.51 | 27.35 |

Note: There are a large number of observations with zero on-site RE, as only 71 sites ever consume any on-site RE. Of those, 25 sites did not begin to do so until after 2017.

## 5. Econometric Strategy

### 5.1 Overall Effect of RE Adoption

To identify the impact of adopting RE on EE, we estimate the following fixed-effects model:

$$\begin{aligned}\log(EnergyDV_{it}) = \beta\, RE\%_{it} + \gamma\, Prod_{it} + \xi_1\, \bar{Cost}_{is}^{F} + \xi_2\, \bar{Cost}_{is}^{R} \\ + \mu_m + \theta_s + \nu_{reg}\, Reg_i \times s + \nu_{cat}\, Cat_i \times s + \eta_i + \epsilon_{it}.\end{aligned} \tag{2}$$

In eq. (2), $EnergyDV_{it}$ denotes the measure of EE, either $Energy$ or $EPTOP$ defined in Section 4.2.2, by site $i$ at month-time index $t \in \{1, \ldots, 72\}$. As defined in Section 4.2.1, our independent variable of interest is $RE\%_{it}$; $Prod_{it}$ is the control for production quantities, which can take multiple transformations—baseline, log, or squared—in each of our models; $\bar{Cost}_{is}^{F}$ and $\bar{Cost}_{is}^{R}$ capture the average cost of fossil and renewable energy, respectively, at site $i$ in year $s$ for $s \in \{2015, \ldots, 2020\}$. We include month fixed effects $\mu_m$ for $m \in \{Feb, \ldots, Dec\}$ to account for seasonality, year fixed effects $\theta_s$, site fixed effects $\eta_i$, region-specific and product-category-specific annual time trends $Reg_i \times s$ and $Cat_i \times s$, where $Reg_i$ and $Cat_i$ are region and product category indicators for site $i$ (we have 8 regions and 13 product categories). Note that year $s$, $Reg_i$, and $Cat_i$ do not appear in the model individually because they are absorbed by the time and site fixed effects. We cluster the standard errors at the site level to account for serial autocorrelation and correct for heteroskedasticity.

In order to estimate the effect of RE adoption on EE, we need to identify $\beta$ in eq. (2). This requires that the variation in $RE\%$ be exogenous, i.e., uncorrelated with the error $\epsilon$. Naturally, there are a few challenges. First, site managers may differ in their attitudes towards RE, and sites may differ in their ability to acquire RE due to regional differences. For example, RE make up a much larger proportion of energy generation in Europe than in Africa, and local residents differ significantly in their awareness of climate change (Lee et al. 2015). We address this by taking advantage of our panel structure and including site fixed effects ($\eta_i$). Site managers are assigned to a single site so our fixed effects are able to control for all time invariant characteristics of both the site and site manager that may be correlated with both RE sourcing and EE. These include both observed and unobserved factors such as manager attitudes and abilities, as well as site location, size, product type, political/business climate among other characteristics.

Second, there are global trends and shocks that may lead to unobserved changes in our variables of interest. To address this issue, we employ time controls at multiple levels. We include year fixed effects ($\theta_s$). In our context, these effects account for unobservable shocks to RE and EE that change over time, but are constant over sites, e.g., macroeconomic shocks that affect global demand. We also include regional and product category time trends. Regional time trends ($\nu_{reg}$) parse out localized changes in EE happening over time due to unobserved factors, such as legislation mandating improvements in EE. Category-specific time trends ($\nu_{cat}$) capture any potential changes in production technology that may had led to changes in EE. We control for both of these by interacting year with the region and product category indicators.

### 5.2 RE Acquisition Approaches and EE

To understand how heterogeneity in RE acquisition can impact EE, we segment RE share for each site $i$ in each period $t$ into on-site generation and off-site purchase, which are captured by $RE\%_{it}^{OnSite}$ and $RE\%_{it}^{Buy}$, respectively. We further segment off-site purchases into PPA and REC ($RE\%_{it}^{PPA}$ and $RE\%_{it}^{REC}$, respectively). Replacing $RE\%_{it}$ in eq. (2) with these variables that capture the percentage of each type of sourcing, we reestimate the model in eq. (2) and compare the results.

We also estimate an alternative specification. While all but one site adopted RE, there is meaningful variation in their RE acquisition strategies during our sample period: some sites installed on-site generation capacity while others did not. For each site in each year, we calculate the annual on-site RE generation as a percentage of annual energy consumption. For all sites, this percentage is non-decreasing, and we consider site $i$ to have installed on-site generation in year $s$ if on-site RE exceeds 1% of its annual energy use in year $s$. Note that while we have monthly observations, we aggregated them in forming our treatment and control groups to account for potential seasonality in some generation technologies like solar power. We did not use 0% as the cutoff because some sites reported tiny on-site RE—e.g., from solar lights at parking lots—which did not support plant production. We utilized slightly lower and higher cutoffs in our analysis, and the results are robust.

We estimate the following difference-in-differences specification:

$$\begin{aligned}\log(EnergyDV_{it}) = {} & \beta_1\, RE\%_{it} + \beta_2\, OnSite_{it} + \delta\, RE\%_{it} \times OnSite_{it} \\ & + \gamma_1\, Prod_{it} + \xi_1\, \bar{Cost}_{is}^{F} + \xi_2\, \bar{Cost}_{is}^{R} \\ & + \mu_m + \theta_s + \nu_{reg}\, Reg_i \times s + \nu_{cat}\, Cat_i \times s + \eta_i + \epsilon_{it},\end{aligned} \tag{3}$$

where $OnSite_{it}$ is the indicator of whether site $i$ has installed onsite generation by time $t$. The key coefficients of interest are $\beta_1$ and $\delta$: $\beta_1$ estimates the effect of RE adoption on EE if RE is acquired only via PPA and/or REC, whereas $\delta$ estimates the change in that effect after a site installs on-site RE generation.

There are potential issues with endogenity with respect to whether and when a site elects to install on-site generation. One possibility is that managers who are more proactive about on-site generation are also more cognizant of EE. We address this by utilizing an instrumental variable (IV) approach. We leverage geographical variation in sites' location across countries, which leads to varying RE capacity and generation within country. All manufacturing sites were built before 2011, and the locations were selected for economic reasons unrelated to the availability of onsite generation technology. Therefore, the country's capacity and generation is random and uncorrelated with EE, except through easing the barriers to installing generation. That is, countries with significant RE capacity and generation are likely to be ones where it is easiest to install private generation.

We utilize data from two sources for our instruments. For capacity, we pull data from the International Renewable Energy Agency (IRENA) statistics on installed electricity capacity. Using historical data, we calculate a three-year percentage change in RE capacity (i.e., divide the difference between current and three-year lagged capacity by the three-year lagged capacity). For generation, we utilize the EIA international database on electricity generation. The data breaks down generation by fuel source for each country over time. We parameterize generation as the annual non-hydroelectric RE generation, and we take the natural logarithm to adjust for scale and skewness. We instrument for our two endogenous regressors $OnSite$ and $OnSite \times RE\%$ using these two instruments and their respective interactions with $RE\%$.

## 6. Results

This section presents the results from estimating the models in Section 5. The robustness of the results are verified in Section 7, and the mechanisms driving these results are analyzed in Section 8.

### 6.1 RE and EE

We estimate the fixed-effect model in eq. (2) using ordinary least squares. The results of eight alternative specifications (differing in dependent variables and control variables) are shown in Table 2. We find that, consistent across all specifications, increasing the proportion of energy from renewable sources leads to a decrease in energy consumption (either total or per ton of production), i.e., an improvement in EE. Specifically, based on the results for EPTOP in columns 5 to 8, we find that using RE to meet 10% more of a site's energy demand led to an additional 2.0% improvement in EE—in addition to the time trends captured by $\theta_s$, $\nu_{reg}$, and $\nu_{cat}$, as well as seasonal effects. The results are robust when analyzing total energy (columns 1 to 4) as well as controlling for effects of energy cost and non-linear effects of production. Thus, our results support Hypothesis 1b. Sites shifting toward renewable sources of energy also experience increased EE. This is an added, economically significant benefit of RE that is typically unaccounted for by corporations adopting RE.

### 6.2 Impact of RE Acquisition Approach on EE

The consistent effect of RE adoption on EE observed in Table 2 is encouraging, but sites can acquire RE in various ways. This section analyzes the model discussed in Section 5.2, which captures

Table 2: Impact of RE Adoption on EE

| | *Dependent Variable* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | log(Energy) | | | | log(EPTOP) | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| RE% | −0.304* | −0.222*** | −0.313** | −0.220*** | −0.207** | −0.197*** | −0.205** | −0.202*** |
| | (0.156) | (0.072) | (0.147) | (0.074) | (0.085) | (0.070) | (0.085) | (0.072) |
| log(Prod) | | 0.505*** | | 0.505*** | | 0.059 | | 0.059 |
| | | (0.062) | | (0.062) | | (0.042) | | (0.042) |
| Prod | | | 0.0002*** | | | | −0.00003*** | |
| | | | (0.00003) | | | | (0.00001) | |
| $\text{Prod}^2$ | | | −0.000*** | | | | 0.000*** | |
| | | | (0.000) | | | | (0.000) | |
| $\bar{\text{Cost}}^F$ | | | | 0.001 | | | | −0.0003* |
| | | | | (0.001) | | | | (0.0002) |
| $\bar{\text{Cost}}^R$ | | | | 0.00000 | | | | 0.0001 |
| | | | | (0.0002) | | | | (0.0001) |
| Site FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Trends | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 13,176 | 13,176 | 13,176 | 13,176 | 13,176 | 13,176 | 13,176 | 13,176 |
| Adjusted $R^2$ | 0.816 | 0.920 | 0.850 | 0.920 | 0.831 | 0.837 | 0.837 | 0.837 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

heterogeneous effects across RE acquisition approaches. The results are reported in Table 3. Given the consistency of the results when analyzing total and normalized energy, we focus on $EPTOP$ as our dependent variable for ease of exposition.

We estimate the model in eq. (2) with $RE\%$ replaced by its components. As shown in Table 3 columns 1 to 2, we observe that RE purchases ($RE\%^{Buy}$), rather than direct generation ($RE\%^{OnSite}$), are driving the EE gains. Upon further segregating RE purchases, we find no statistically significant difference between directly contracting for RE from producers through PPAs ($RE\%^{PPA}$) and purchasing RECs ($RE\%^{REC}$).

Then, we estimate the model in eq. (3) and delve into the differences in the effect of RE adoption on EE for sites with differing acquisition strategies. From Table 3 columns 3 to 4, we see that the sites that installed on-site RE generation had a significantly different outcome for their EPTOP. Note that the marginal effects are such that sites without on-site generation saw a 2.8%–3.8% ($\beta_1$ for $RE\%$) additional improvement in EE when using RE to meet 10% more of sites' energy demand. In contrast, sites with on-site generation achieved at most a 0.6% ($\beta_1 + \delta$ for $RE\% + RE\% \times OnSite$)

improvement or even a decline in EE for the same change in RE. Our results are robust under the IV specification (see Section 5.2) economically and statistically. The first-stage regressions (IV-FS), along with the reduced form (RF) for the OLS-IV model, are shown in Table 4. The conditional $F$-test for the individual first-stages show strong relevance of the instruments, and the Kleibergen-Paap Wald $F$-stat for weak instruments is 13.48, which is above critical thresholds.

Table 3: Impact of RE Sourcing Heterogeneity on EE

| | *Dependent Variable* | | | |
|---|---|---|---|---|
| | log(EPTOP) | | | |
| | (1) OLS | (2) OLS | (3) OLS | (4) OLS-IV |
| RE%$^{Buy}$ | −0.141*** | | | |
| | (0.053) | | | |
| RE%$^{PPA}$ | | −0.142*** | | |
| | | (0.051) | | |
| RE%$^{REC}$ | | −0.136* | | |
| | | (0.076) | | |
| RE%$^{OnSite}$ | 0.150 | 0.151 | | |
| | (0.106) | (0.107) | | |
| RE% ($\beta_1$) | | | −0.275*** | −0.380*** |
| | | | (0.088) | (0.110) |
| OnSite ($\beta_2$) | | | −0.037 | −0.058 |
| | | | (0.027) | (0.083) |
| RE%×OnSite ($\delta$) | | | 0.206*** | 0.479** |
| | | | (0.066) | (0.241) |
| Site, Month, Year FE | Yes | Yes | Yes | Yes |
| Time Trends | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes |
| Observations | 13,176 | 13,176 | 13,176 | 9,744 |
| Adjusted $R^2$ | 0.837 | 0.837 | 0.838 | 0.825 |
| *Note:* | | | *p<0.1; **p<0.05; ***p<0.01 | |

Altogether, these results suggest that while direct on-site RE generation requires greater upfront investment, it does not necessarily translate into greater conscientiousness of energy usage and efficiency. One theory is that on-site RE generation may actually lead to less efficiency due to sunk costs—once the infrastructure is built, the marginal cost of RE is minimal compared to purchasing energy from utilities, thus reducing the motivation to achieve further gains through efficiency. We concede though that on-site RE generation represents only a small portion of the RE consumed, and thus we cannot be more concrete in our statements.

Table 4: Instrumental Variable Diagnostics. The first two columns show the first-stage regression results of the instrument on *OnSite* and the third shows the reduced form regression.

| | *Dependent Variable* | | |
|---|---|---|---|
| | OnSite | RE%×OnSite | log(EPTOP) |
| | (IV-FS) | (IV-FS) | (RF) |
| RE% | 0.179** | 0.117 | −0.331*** |
| | (0.079) | (0.105) | (0.096) |
| $\text{Capacity}_3$ | 0.062*** | −0.002 | −0.007 |
| | (0.008) | (0.006) | (0.009) |
| log(Generation) | 0.028 | −0.042* | −0.023 |
| | (0.041) | (0.024) | (0.039) |
| RE%×$\text{Capacity}_3$ | −0.003 | 0.063*** | 0.038** |
| | (0.022) | (0.015) | (0.017) |
| RE%× log(Generation) | −0.022 | 0.055** | 0.026* |
| | (0.019) | (0.027) | (0.015) |
| Site, Month, Year FE | Yes | Yes | Yes |
| Time Trend | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes |
| Observations | 9,744 | 9,744 | 9,744 |
| Adjusted $R^2$ | 0.906 | 0.859 | 0.825 |
| Cond. F-Stat | 133.07 | 13.35 | - |

*Note:* *p<0.1; **p<0.05; ***p<0.01

## 7. Robustness Checks

To strengthen the validity of our results, we perform a number of robustness checks on various factors that may influence our results. As we describe in detail below, our additional analyses test for generalizability using a longer time frame, alternative model specifications and estimation methods, as well as implementing coarsened exact matching to adjust for potential baseline differences between sites. Overall, the results give us confidence that our findings are robust and not sensitive to our assumptions and choice of specifications.

### 7.1 Alternative Specifications

#### 7.1.1 Threshold Model

In our main analysis, we treat RE sourcing as a continuous variable. That is, we implicitly assume that each marginal percentage point increase in RE has a constant effect on EE. However, it is possible that the impact is discrete, i.e., a threshold response rather than intensity. When a site achieves a certain milestone in its RE percentage, there may be internally or publicly circulated news reports that elevate the sentiment, creating a threshold response. To capture this, we examine an alternative model as follows.

First, we divide the sites into treatment and control groups based on whether the site has ever achieved some renewable threshold $\bar{RE}\%$. We then implement coarsened exact matching on the RE percentage, production, and costs in 2015. Finally, we estimate a difference-in-differences model with a binary variable *Green*, which takes value 1 when $RE\% > \bar{RE}\%$ and 0 otherwise. That is, we compare the relative change in EE before and after a site goes green to its counterpart, which has never gone green. The results are shown in Table 5, where we have varied $\bar{RE}\%$ in a range from 20% to 60%. As all sites sourced some energy from renewable sources, we determined the lower and upper bounds based on the $10^{th}$ and $50^{th}$ percentiles (rounded to the nearest 5%) respectively. Although not an absolute delineation between sites that have gone green and those that have not, the coefficients actually provide us with a conservative estimate of the impact because the control group is potentially also receiving some treatment effect from having had some RE. Note that as the threshold increases, there are more sites in the control group for the matching step and thus an increase in the number of observations. The results are consistent with our main findings.

Table 5: Threshold parameterization of changes in RE on EE.

| | *Dependent Variable* | | | | |
|---|---|---|---|---|---|
| | log(EPTOP) | | | | |
| | 20% | 30% | 40% | 50% | 60% |
| Green | $-0.106^{**}$ | $-0.087^{**}$ | $-0.102^{**}$ | $-0.083^{**}$ | $-0.096^{**}$ |
| | (0.049) | (0.043) | (0.039) | (0.038) | (0.043) |
| log(Prod) | $0.142^{**}$ | $0.122^{**}$ | $0.115^{**}$ | $0.115^{**}$ | $0.116^{**}$ |
| | (0.062) | (0.055) | (0.054) | (0.054) | (0.054) |
| $\bar{\text{Cost}}^F$ | 0.001 | 0.0005 | 0.0005 | 0.001 | 0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| $\bar{\text{Cost}}^R$ | 0.00003 | 0.00002 | 0.00002 | 0.00002 | $-0.00001$ |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| Site, Month, Year FE | Yes | Yes | Yes | Yes | Yes |
| Time Trend | Yes | Yes | Yes | Yes | Yes |
| Observations | 5,976 | 7,200 | 7,488 | 7,632 | 7,848 |
| Adjusted $R^2$ | 0.817 | 0.827 | 0.848 | 0.854 | 0.846 |
| *Note:* | | | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

#### 7.1.2 Hierarchical Model

We also consider a random effects modeling approach (Mundlak 1978, Certo et al. 2017) for a couple of reasons. First, business organizations are generally organized around a hierarchy where senior managers may be responsible for overseeing and directing multiple managers or sites. There may be geographical, as well as functional (e.g., product categories), reporting matrices, such that sites belong to two non-nested levels: region and product. For example, there may be a director of North American operations who covers all sites on the continent, as well as a director of household goods who oversees any sites that produces products within this category across the globe. Our sample firm operates in a matrix structure like this, where there are directors responsible for geographical regions as well as directors that cover product categories. Second, by estimating a within-between formulation, we can capture variation both at the longitudinal (i.e., within-site, which is the basis of our main analysis), as well as cross-sectional (i.e., between-sites).

The longitudinal variation allows us to identify how EE responds to the changes in RE sourcing over time. The cross-sectional captures differences in energy sourcing decisions at a given point in time. This likely reflects systematic differences across sites that are associated with RE sourcing.

To capture this hierarchical structure, we estimate a multi-level model. We begin with a two-level specification (S) where we capture the structure of repeated observations over time of the same individual sites, i.e., we model a site random effect rather than the fixed effect of our main analysis. Next we expand this to a three-level model, under which we examine three specifications. We create a nested structure where individual sites belong to i) a region (R) or ii) a product category (P). Finally, we allow both region and product category cross effects. The results are again consistent with our main findings and are shown in Table 6. Interestingly, we find that on-site generation actually leads to significantly higher EPTOP (lower EE) on-site when analyzing both within and between site variation.

#### 7.1.3 Reverse Causality

Since we are observing EE improvement and RE adoption at the same time, one concern is the potential for reverse causality, i.e., EE improvement drives RE adoption rather than vice versa as we proposed. We do not believe this is an issue for the following reason. First, effort in EE improvement existed long before renewable PPA, REC, and on-site RE generation became popular; the barriers to EE have been discussed for decades (see Section 2). Second, PPAs and on-site generation infrastructure development are long-term decisions, while energy consumption behaviors are realized at the time of production. PPAs between a producer and consumer generally span over

Table 6: Hierarchical Specification. **S** captures site random effects. **R** captures regional effects and **P** is for product category, both with nested sites. **R/P** includes both regional and product category cross effects. All specifications include region and product category time trends, as well as month and year fixed effects.

| | *Dependent Variable* | | | | | |
|---|---|---|---|---|---|---|
| | log(EPTOP) | | | | | |
| | RE% | $RE\%^{Buy}$ | $RE\%^{OnSite}$ | $RE\%^{PPA}$ | $RE\%^{REC}$ | $RE\%^{OnSite}$ |
| S | $-0.247^{***}$ | | | | | |
| | (0.013) | | | | | |
| | | $-0.151^{***}$ | $0.162^{***}$ | | | |
| | | (0.013) | (0.040) | | | |
| | | | | $-0.154^{***}$ | $-0.141^{***}$ | $0.163^{***}$ |
| | | | | (0.015) | (0.023) | (0.040) |
| R | $-0.180^{***}$ | | | | | |
| | (0.014) | | | | | |
| | | $-0.205^{***}$ | $0.114^{***}$ | | | |
| | | (0.015) | (0.041) | | | |
| | | | | $-0.211^{***}$ | $-0.188^{***}$ | $0.114^{***}$ |
| | | | | (0.016) | (0.024) | (0.041) |
| P | $-0.141^{***}$ | | | | | |
| | (0.013) | | | | | |
| | | $-0.172^{***}$ | $0.183^{***}$ | | | |
| | | (0.013) | (0.041) | | | |
| | | | | $-0.183^{***}$ | $-0.142^{***}$ | $0.186^{***}$ |
| | | | | (0.015) | (0.023) | (0.041) |
| R/P | $-0.197^{***}$ | | | | | |
| | (0.014) | | | | | |
| | | $-0.232^{***}$ | $0.152^{***}$ | | | |
| | | (0.015) | (0.042) | | | |
| | | | | $-0.240^{***}$ | $-0.207^{***}$ | $0.152^{***}$ |
| | | | | (0.016) | (0.025) | (0.042) |
| *Note:* | | | | | | $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$ |

a decade[6] and are negotiated independent of EE.

To further solidify our findings, we estimate a model with lagged explanatory variables. Lagged variables are often employed to address the reverse causality problem in identification based on the reasoning that current outcomes can not affect an explanatory variable in the past. In our implementation, we examine regressions where our RE sourcing variable is lagged by one year. The results are shown in Table A1 and again are consistent with our main findings.

While we acknowledge that, under most circumstances, lagging an explanatory variable only moves the channel through which endogeneity (reverse causality) acts (Bellemare et al. 2017), we

[6] https://pv-magazine-usa.com/2020/02/04/utility-scale-solar-ppa-pricing-down-4-7-in-2019-with-13-6-gw-of-corporate-deals-signed/

believe our context does not suffer from these concerns due to a combination of our fixed effects identification strategy and the data generating process in our context. Specifically, Bellemare et al. (2017) show that, even in the presence of unobserved confounders, if (i) there are no dynamics among unobservables, and (ii) the lagged endogenous variable is a stationary autoregressive process, then lagging our explanatory variable resolves the endogeneity issues. While we cannot test each of these assumptions directly, using falsification tests, we examine regression residuals as well as the data generating process of our explanatory variable. We find no evidence that the conditions are violated. Specifically, under the correlated augmented Dickey–Fuller test (test statistic: $-7.509$, $p$-value $< 0.01$), we reject the null hypothesis of a unit root and conclude that our explanatory variable is stationary.

Additionally, we test for whether a site's EE in a given year predicts the amount of RE in the following year. We classify sites into quartiles annually based on their EE. Specifically, we consider their relative EPTOP within: i) year (Year); ii) product category-year (P-Year); iii) production-year (Prod-Year); and iv) region-year (Reg-Year). For production-year, we first divide sites into quartiles based on their production in tons, and then determine the EPTOP quartile within each production quartile. As shown in Table 7, we do not find that a site's EE systematically affects its RE decisions.

Table 7: Effect of EE on RE in the following year

| | *Dependent Variable* | | | |
|---|---|---|---|---|
| | RE% | | | |
| | (Year) | (P-Year) | (Prod-Year) | (Reg-Year) |
| $\text{EPTOP}_{Q2}$ | $-0.071$ | 0.006 | 0.001 | $-0.032$ |
| | (0.048) | (0.023) | (0.028) | (0.047) |
| $\text{EPTOP}_{Q3}$ | $-0.041$ | $-0.034$ | $-0.020$ | $-0.065$ |
| | (0.057) | (0.049) | (0.037) | (0.067) |
| $\text{EPTOP}_{Q4}$ | $-0.068$ | $-0.018$ | $-0.033$ | $-0.162^{*}$ |
| | (0.071) | (0.067) | (0.046) | (0.082) |
| Site, Month, Year FE | Yes | Yes | Yes | Yes |
| Time Trend | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes |
| Observations | 10,980 | 10,980 | 10,980 | 10,980 |
| Adjusted $R^2$ | 0.784 | 0.783 | 0.783 | 0.785 |

*Note:* $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

### 7.2 Sample Construction

We implement two additional robustness checks related to our sample. First, we extend our study period back to 2011, at the price of excluding cost as a control variable. Cost data was not collected before 2015 and thus could not be included in the extended period. Second, COVID-19 had significant impacts on manufacturing ranging from site shutdowns to demand distortions. To remove any potential confounding effects, we also fit our model using data excluding 2020. Our results (Table A2) are robust to both of these alternative samples.

Additional, we examine whether the effect may be driven by significant macro events in one particular country. For example, pricing surges due to energy embargoes or supply issues may lead sites to switch their energy source and to institute energy saving initiatives. To test for this, we exclude one country at a time and reestimate our main specifications. Finally, we examine whether manufacturing of specific products may lead to the observed results. Analogously, we drop one product category at a time and reestimate our model. Our results are consistent across the board and anonymized versions are available upon request.

## 8. Mechanism

In this section, we analyze drivers of our results. EE gains can come as a result of behavioral changes or technological/process improvements. To analyze the former, we conduct surveys and interviews to elicit any evidence of changes in attitudes and behaviors. For the latter, we examine funding requests made to HQ for efficiency projects.

### 8.1 Survey

We conducted full length interviews with four managers to develop insight into the gains in EE that we observed. Qualitative evidence suggests that managers became more conscious of their energy usage after having to verify their energy sourcing. Instances of how line operators and employees can be engaged can also help reduce overall energy consumption and improve EE. For example, instilling EE in the minds of employees helps reduce overall energy consumption at the site. At one of the best performing sites (in terms of energy reduction), we asked about specific actions that could be helping improve EE. The managers identified changes in employee practices and instilling the importance of reducing energy consumption as the drivers of this improvement. One specific example described how operators began turning off machines when refilling the wrapping paper reels for final product packing after they understood the value of reducing energy consumption. Installing a new roll would take 5-15 minutes depending on the size of the roll and the specific product type, and this needed to occur up to 10 times per shift.

We were granted permission to conduct a brief survey to verify the generalizability of this channel (behavioral changes) during a quarterly meeting of all site managers. Survey questions, along with the results are shown in Appendix B. The survey questions were asked individually through Microsoft Teams where the next question only appeared after the prior one was answered. Among 103 managers, we found that 71% of them identified improving cost efficiency as the primary driver when asked about their motivations for investing in RE. When given the option to select multiple answers, we found that 94% selected cost efficiency (the highest percentage), while 85% mentioned following the corporate mandate.

To delve into this further, we then asked managers how their attitudes toward EE changed after they started sourcing RE. 74% of managers indicated their focus increased, while interestingly 23% responded that their focus actually decreased. When asked about their perceptions of their employees' attitudes, the results were similar at 77% and 18% respectively.

These results suggest three important managerial insights. First, it provides qualitative support of our main findings that sourcing RE leads to improved EE, and it posits that a greater focus by managers on efficiency, after changes in sourcing, is the mechanism through which this is achieved. Second, the heterogeneity in the responses, specifically the dichotomy on changes in attitudes towards EE, provides support for a more nuanced effect from RE adoption. Third, it is interesting to note that the primary reason that managers consider RE was cost efficiency. Managers seem to believe that investing in RE will help them reduce costs.

We interviewed two of the managers that responded that cost efficiency was the primary driver in order to better understand their reasoning. These managers indicated that after the initial investment, they hoped to realize savings since a new RE generation source had been installed. However, when pushed for further clarification on the amount of RE generation compared to total site consumption, managers had limited information regarding how much energy was being generated by the installation. They also expressed that they no longer needed to worry about EE after moving RE generation on site. This is consistent with prior work on the rebound effect (Berkhout et al. 2000) in the context of onsite generation of RE. Managers seem to believe that after the initial investment, "free" energy obviates the need for efficiency improvement.

These findings present an opportunity for future research as there seems to be a disconnect between managers that are responsible for authorizing investments in RE and the engineering teams that size the generation equipment. To comply with rules and maintain a reasonable budget, plants rarely size onsite RE to give them all their energy demand. Therefore, it is important for managers to understand this difference and continue to emphasize the importance of EE even if they have onsite RE generation.

### 8.2 Capital Expenditures

The survey results provide qualitative evidence of our proposed channel. To further expand this and identify quantitative evidence, we analyze data on managers' capital expenditures on EE and energy monitoring as a function of their RE proportion. Each site has its own operating budget and is responsible for managing investments and operations at the site level. However, starting in 2016, corporate headquarters (HQ) allotted a certain budget that could be used on projects to enhance the sustainability performance at the site. Using a standard form, each site described their proposal, detailing what the project would cost and its financial and energy savings impact.

This data was compiled, and every quarter a team of managers met to decide on which projects to fund. The team of managers that handled the capital allocation were all based at HQ and none were site managers (the proposal submitters). This data was managed at HQ and continually updated. The resultant file contained information on all the proposals that were submitted, which projects were approved, and all the relevant information. Since each proposal had to be submitted using a form, the file allows us to compare all the projects.

We observe all capital funding requests made by site managers from 2016 onwards. Of these, we examine the subset of those requests relating to EE and energy monitoring. For each request, we observe the site, project category, project name, request date, and approval date. While we do not observe detailed project descriptions, the project names allow us to validate the categorization at a high level. A sample of project names are shown in Table A3 for reference.

We analyze the impact of the one-year change in RE sourcing on the cumulative number of requested energy savings and meter projects in the following 12 months. Specifically, we estimate the following:

$$\log(TotalRequests)_{it} = \beta\,\Delta RE\%_{it} + \gamma\,\log(Prod_{it}) + \xi_1\,\bar{Cost}^F_{it} + \xi_2\,\bar{Cost}^R_{it} + \eta_i + \epsilon_{it}, \tag{4}$$

where $TotalRequests$ is the cumulative sum of requests from 2015, $\Delta RE\%$ is the one year change in percentage of energy drawn from RE sources, $Prod$ is the annual production in tons, $\bar{Cost}^F$ and $\bar{Cost}^R$ are the average annual costs of fossil and renewable energy per kilowatt-hour respectively, and $\eta$ is the site fixed effect.

We estimate the coefficients of eq. (4) using both OLS and a zero-inflated Poisson (ZIP) model. We include the ZIP model because of the large number of zero counts in our data. That is, many site managers did not submit any requests for support to fund EE projects. Note that site managers could still fund improvements out of their operating budgets, but we are not able to observe these.

Under the ZIP model, intuitively the model allow us to separately estimate the willingness to request funding as part of the logit model and the number of requests made, conditional on having made a request, as a Poisson count model. The results are shown in Table 8.

Table 8: Changes in total funding requests submitted in response to changes in sourcing from RE.

| | *Dependent Variable* | |
|---|---|---|
| | log(TotalRequests) | TotalRequests |
| | *OLS* | *ZIP* |
| $\Delta$RE% | 0.207*** | 0.322** |
| | (0.050) | (0.143) |
| Observations | 800 | 800 |
| Site FE | Yes | Yes |
| Controls | Yes | Yes |
| Adjusted $R^2$ | 0.776 | – |
| Log Likelihood | – | −659.2 |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 | |

We find that in the year following an increase in RE sourcing, the number of funding requests for EE projects increases significantly. Specifically, we find that a 10% increase in RE leads to a 2.1% increase in project proposals under OLS and 0.032 (2.4%) additional requests based on the ZIP model. While the figures may seem small, sites had the option to apply for funds *or* to fund projects out of their operating budgets, which has less HQ oversight. Therefore these requests represent not only an increased interest in EE projects, but also increased effort and attention on these projects.

## 9. Conclusion

EE and RE are two pillars for achieving energy sustainability from both the demand and supply sides. Recent years have seen a rise in RE adoption, but a slowdown in EE improvement. Many have investigated the reasons for the slowdown; a common perception is that RE investment has lured capital away from EE projects. Our research offers a new perspective on the relationship between the two pillars based on empirical evidence from 183 sites of a global manufacturing firm. In particular, our investigation shows when and how RE sourcing can actually increase EE improvement. On aggregate, the U.S. spent $1.2 trillion on energy in 2019, of which 32.4% was by the industrial sector (Center for Sustainable Systems 2021). If our findings for the focal industrial firm can be generalized to the industrial sector, a 10% increase in RE sourcing in the sector would have led to at least 2.2% reduction in energy consumption (refer to Table 2), which translates to at least $8.6 billion savings in one year alone.

Our key finding that RE purchases may increase EE improvement has important implications.

First, for corporations that are expanding their RE sourcing, purchasing RE can yield the added benefit of reminding managers of the supply-side cost and the importance of demand-side management, i.e., improving EE. On-site RE generation provides almost zero marginal cost of energy, which may send a false signal for the effort on EE. For firms that have already built on-site RE generation, it is important to educate and remind managers and workers that the total cost of RE do not vary much with respect to how they are procured and that being more efficient on the demand side is always the best cost-savings method.

Second, for policymakers, designing policies to encourage indirect RE procurement would be desirable. This means that policymakers should encourage third-party RE generation and standardize PPAs to provide more revenue certainty rather than leaving PPAs entirely to bilateral negotiation. Policymakers can also consider phasing out favorable policies for on-site RE generation and direct more subsidies toward independent RE producers who are in the best position to maintain facilities. RE is costly and EE endeavor should never need to be renewed.

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# Appendix

## A. Additional Tables

Table A1: 12 month lagged regressions

| | *Dependent Variable* | | |
|---|---|---|---|
| | log(EPTOP) | | |
| | (1) | (2) | (3) |
| $RE\%_{12}$ | $-0.141^{***}$ | | |
| | (0.054) | | |
| $RE\%_{12}^{Buy}$ | | $-0.146^{**}$ | |
| | | (0.058) | |
| $RE\%_{12}^{PPA}$ | | | $-0.132^{**}$ |
| | | | (0.051) |
| $RE\%_{12}^{REC}$ | | | $-0.178^{**}$ |
| | | | (0.082) |
| $RE\%_{12}^{OnSite}$ | | $-0.080$ | $-0.081$ |
| | | (0.058) | (0.059) |
| Site, Month, Year FE | Yes | Yes | Yes |
| Time Trend | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes |
| Observations | 10,980 | 10,980 | 10,980 |
| Adjusted $R^2$ | 0.866 | 0.933 | 0.895 |
| *Note:* | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 | | |

Table A2: Sample Robustness Tests

| | *Dependent Variable* | | | | | |
|---|---|---|---|---|---|---|
| | Extend to 2011 | | | Exclude 2020 | | |
| | log(EPTOP) | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| RE% | −0.147*** | | | −0.155*** | | |
| | (0.055) | | | (0.055) | | |
| $RE\%^{Buy}$ | | −0.172*** | | | −0.179*** | |
| | | (0.059) | | | (0.059) | |
| $RE\%^{PPA}$ | | | −0.175*** | | | −0.195*** |
| | | | (0.060) | | | (0.063) |
| $RE\%^{REC}$ | | | −0.163** | | | −0.145* |
| | | | (0.082) | | | (0.078) |
| $RE\%^{OnSite}$ | | 0.019 | 0.019 | | −0.006 | −0.003 |
| | | (0.074) | (0.074) | | (0.076) | (0.077) |
| Site, Month, Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Trend | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 19,560 | 19,560 | 19,560 | 10,980 | 10,980 | 10,980 |
| Adjusted $R^2$ | 0.842 | 0.842 | 0.842 | 0.845 | 0.846 | 0.846 |
| *Note:* | | | | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

## B. Managerial Survey Results

1. What were your motivations for investing in renewable energy? (select primary)
   (i) Be more environmentally friendly - 2%
   (ii) Achieve emissions targets - 6%
   (iii) Improve cost efficiency - 71%
   (iv) Following corporate mandate - 21%

2. What were your motivations for investing in renewable energy? (select multiple)
   (i) Be more environmentally friendly - 31%
   (ii) Achieve emissions targets - 43%
   (iii) Improve cost efficiency - 94%
   (iv) Following corporate mandate - 85%

3. As a manager, after you began sourcing renewable energy, how did your attitude towards energy efficiency change?
   (i) No Change - 3%
   (ii) Increase focus on energy efficiency - 74%
   (iii) Decrease focus on energy efficiency - 23%

4. How did the attitude of the plant employees toward energy efficiency change after investing in renewable energy?
   (i) No Change - 5%
   (ii) Increase focus on energy efficiency - 77%
   (iii) Decrease focus on energy efficiency - 18%

## C. Capital Projects

Table A3: Sample Capital Improvement Project Proposals

| **Project Type** | **Project Name** |
|---|---|
| Energy Savings | Gas Consumption Optimization in Boiler Room |
| Energy Savings | Thermal Insulation on Hotwater Boiler |
| Energy Savings | Energy Efficiency Improvement in Evaporation and Tower |
| Energy Savings | Using residual heat in process |
| Energy Savings | Heat recovery - rework room |