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Better sustainability assessment of green buildings with high-frequency data

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Reducing electricity consumption through green building certification is one key strategy for achieving environmental sustainability. Traditional assessments of the environmental benefits of green buildings rely on electricity consumption data at an aggregated level (such as monthly). Using such data can bias assessment results because marginal emissions factors vary throughout the day. We use panel data on hourly energy usage at the individual-building level from 2013–2016 in Arizona to provide a more accurate sustainability assessment for green buildings. For both Energy Star and Leadership in Energy and Environmental Design buildings, our estimated savings suggest that the majority of electricity savings in summer happen during electric load system peak hours. The estimated hourly savings and hourly marginal emissions damages reveal additional environmental gains in green-certified buildings. We show that traditional methods that ignore the intra-day timing of savings can underestimate the environmental benefit of green commercial buildings by 95%. We also demonstrate that our findings can be generalized to a broader geographical context.

Electricity production is responsible for the largest share of greenhouse gas emissions and for more than 60% of SO_2 emissions[1]. Other major air emissions from electricity production include NO_x, particulate matter, mercury and other air toxics[2]. Reducing electricity consumption through improving energy efficiency is a key strategy to reduce electricity production and the associated air and greenhouse gas emissions. Commercial buildings are particularly important for energy efficiency because they are responsible for 36% of total electricity consumption in the United States[3]. Two voluntary green building certification systems encourage the investment of energy-efficient and sustainable buildings: (1) Energy Star and (2) Leadership in Energy and Environmental Design (LEED). Various types of incentives and policies for building energy efficiency improvements exist, such as direct rebates, building codes, real property tax exemption for green-certified commercial buildings, and expedited permitting processes for new buildings and major renovations receiving LEED certification[4]. Since 1995, the number of commercial buildings that have obtained these green certificates has increased dramatically.

Most existing studies that evaluate the environmental gains from green commercial buildings using a large sample of buildings rely on aggregate energy consumption data at the monthly or even yearly level[5–9]. Some of these studies report modest energy savings from green commercial buildings, while others do not find any savings. Such findings are used to support policy arguments against green building incentives. Besides, it is common knowledge that every time data are aggregated, potentially valuable information is lost. Due to technology and storage limitations, disaggregated data are not often available. Yet, benefits from green buildings do not only derive from an aggregated level of consumption. When higher-frequency data become available, information previously lost through aggregation can be recovered to shed additional light on long-debated questions. While existing studies are useful from an energy management perspective, they cannot be used to estimate intra-day hourly energy savings and thus are not particularly valuable for environmental sustainability assessment. The fuel types for electricity generation vary throughout the day[10]. This has crucial implications for both environmental sustainability and for an economic benefit assessment of green buildings.

Both the season and the time of day determine the environmental costs associated with electricity consumption due to varying marginal emission factors[10]. Energy savings during hours when fossil fuels are used as the marginal-generation fuel source have larger environmental benefits than savings during hours when power is generated by renewable energy. In other words, even if green buildings do not consume less electricity than their traditional counterparts, if their hourly electricity usage profile shifts, there would still be positive or negative impacts on environmental sustainability. Such empirical assessment can only be conducted with higher-frequency data. In terms of evaluating the economic benefits, green commercial building technologies are important for peak power grid load reduction[11,12]. Electricity providers need to switch peaking generation power plants on and off frequently to satisfy demand fluctuations. The associated negative results to electricity providers include accelerated deterioration to expensive equipment, higher operation costs and a longer recovery period of upfront capital investment[13,14]. All of these effects can be mitigated if the energy savings from energy efficiency improvements occur during peak hours instead of non-peak hours (or occur more during peak hours).

Examining the timing of electricity savings (for example, by hour of day) has only become possible in recent years as the recent deployment of smart meters makes high-frequency electricity usage data available. In 2014, 58.8 million smart metering infrastructure installations provided high-frequency energy demand data (often in 15 min intervals) for US electricity utility companies and their customers[15]. Smart meters are in 43% of the country and are quickly becoming the norm[16]. Yet, energy efficiency evaluations that apply advanced computational methods to large-sample smart meter data remain rare[17,18]. There are three exceptions. Two such studies are Boomhower and Davis[18] and Novan and Smith[19], which focus on residential buildings instead of commercial buildings. Another such study is Burlig et al.[20], which focuses on energy

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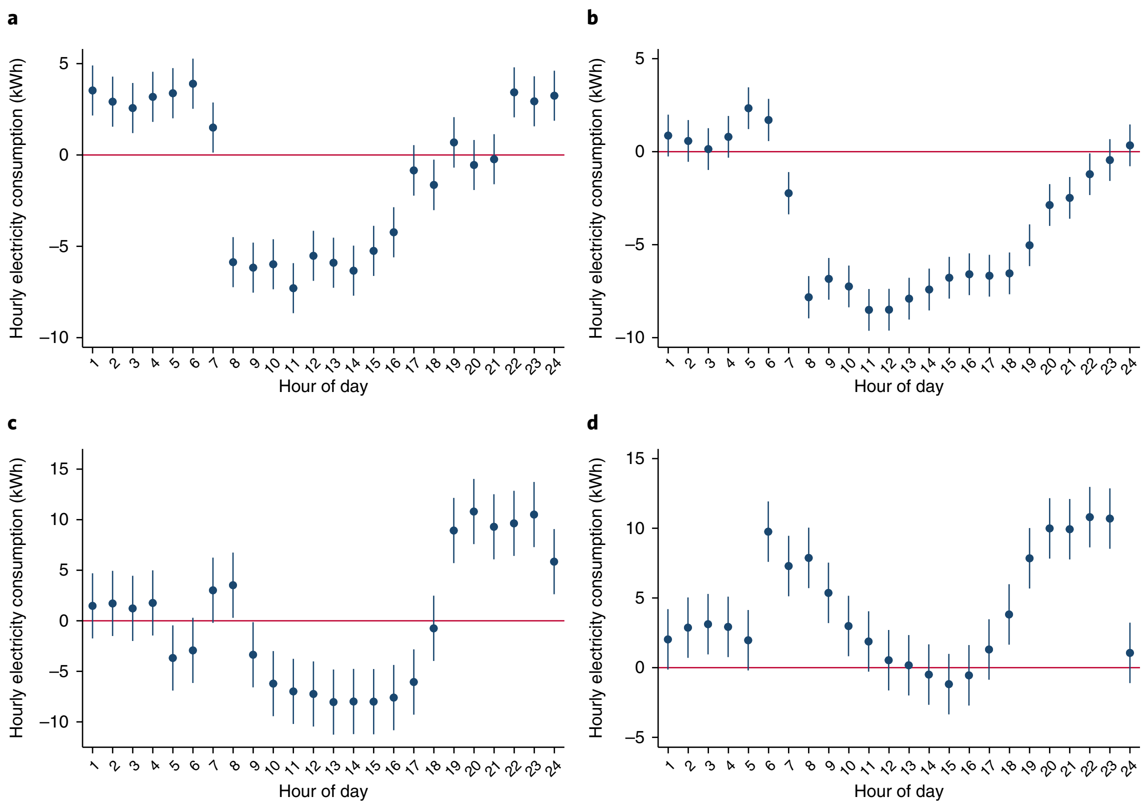

Fig. 1 | Intra-day electricity savings by hour using a subsample with both pre- and post-treatment hourly consumption data. a–d, Coefficients of the interaction terms of Energy Star (**a** and **b**) or LEED certification (**c** and **d**) dummy variables and dummy variables indicating the hour of the day in summer (**a** and **c**) and winter (**b** and **d**). The solid dots indicate the magnitudes of the coefficients, while the vertical lines show the 95% confidence intervals. The values of the coefficients show the change in energy consumption at a particular hour due to green buildings. Negative values indicate electricity savings.

efficiency investments in public kindergarten to twelfth-grade school buildings in California. Our paper improves on these studies by providing empirical evidence showing that higher-frequency energy data improve the accuracy of environmental impact evaluations. It also covers a wider range of commercial building types and geographical areas.

This study investigates the energy savings by hour of day for green-certified commercial buildings. The detailed data add a valuable new dimension to green building sustainability studies. Then, using the estimated hourly savings and hourly marginal emissions damages from CO_2, SO_2, NO_X and particulate matter, we assess more precisely the environmental gain from green buildings. Building on the empirical results from Arizona, we also assess environmental sustainability of green-certified buildings in all other continental US states.

We examine the LEED- and Energy Star-certified commercial buildings (green buildings hereafter) in the Phoenix metropolitan area of Arizona (see Supplementary Fig. 1 for the locations and distribution of business customers located in certified green buildings as of 2016). We analyse three components: the estimation of the hourly electricity usage profiles of green buildings, an environmental impact assessment for green buildings in Arizona, and environmental impact assessments by industry and for other regions. Because there are many similar growing cities exposed to warm temperatures worldwide[21,22], our results have broader applicability beyond Phoenix. We evaluate the electricity savings by hour of day from Energy Star- and LEED-certified commercial buildings, using account-level high-frequency (hourly) usage data provided by a major Arizona electricity utility company for 2013–2016. Data availability allows for more comprehensive and rigorous analysis. Methodologically, this study controls for confounding factors and endogeneity issues through statistical matching methods and panel regressions using a rich set of fixed effects. Consequently, the results' robustness affords engineers, policymakers and investors greater confidence when making relevant decisions.

Results of econometric models

Participating in a LEED or Energy Star programme is a voluntary decision and this raises the issue of selection bias. For example, more energy-savvy or environmental-conscious occupants might be more likely to choose to locate in a green building. In addition, potential omitted variable issues can also cause endogeneity concerns. Examples of these confounding factors include building codes, changes of building occupancy, and changes to electricity pricing plans, which can influence both the selection of green certification and energy consumption.

We used a combination of matching and difference-in-differences approaches to address the potential endogeneity issues, following the approach by Fowlie et al.[23]. The nearest-neighbour-matching method described in the Methods yielded a sample of 33 and 8 pairs of control and treatment customers for the analysis of Energy Star and LEED, respectively. Control customers are business customers occupying non-green-certified buildings, and treatment customers refer to those in green-certified buildings. To conduct difference-in-differences analyses, both pre- and post-certification data were needed. Hence, our main analysis only examines those buildings that obtained green certificates between 2013 and 2016 due to the availability of hourly data. We list the summary statistics of pre-certification hourly electricity consumption (kWh) of both treatment and control customers and calculate the balancing statistics to demonstrate that the treatment and control groups are comparable (see Supplementary Tables 1–4). We also plot the

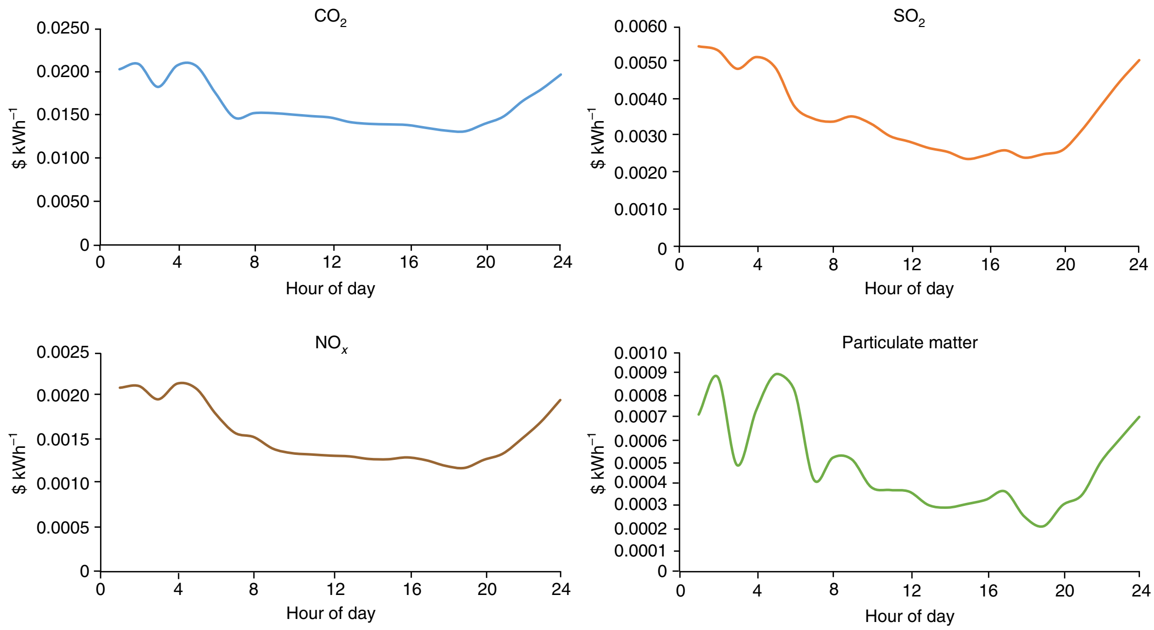

Fig. 2 | Marginal damages for the WECC (in US dollars from the year 2000) from carbon and air emissions by hour of day. The marginal damage factor from a pollutant represents the additional damage (negative impact of pollution as measured in dollar values) caused by the emission of this pollutant from an additional 1 kWh electricity usage in a region. Data from ref. [26].

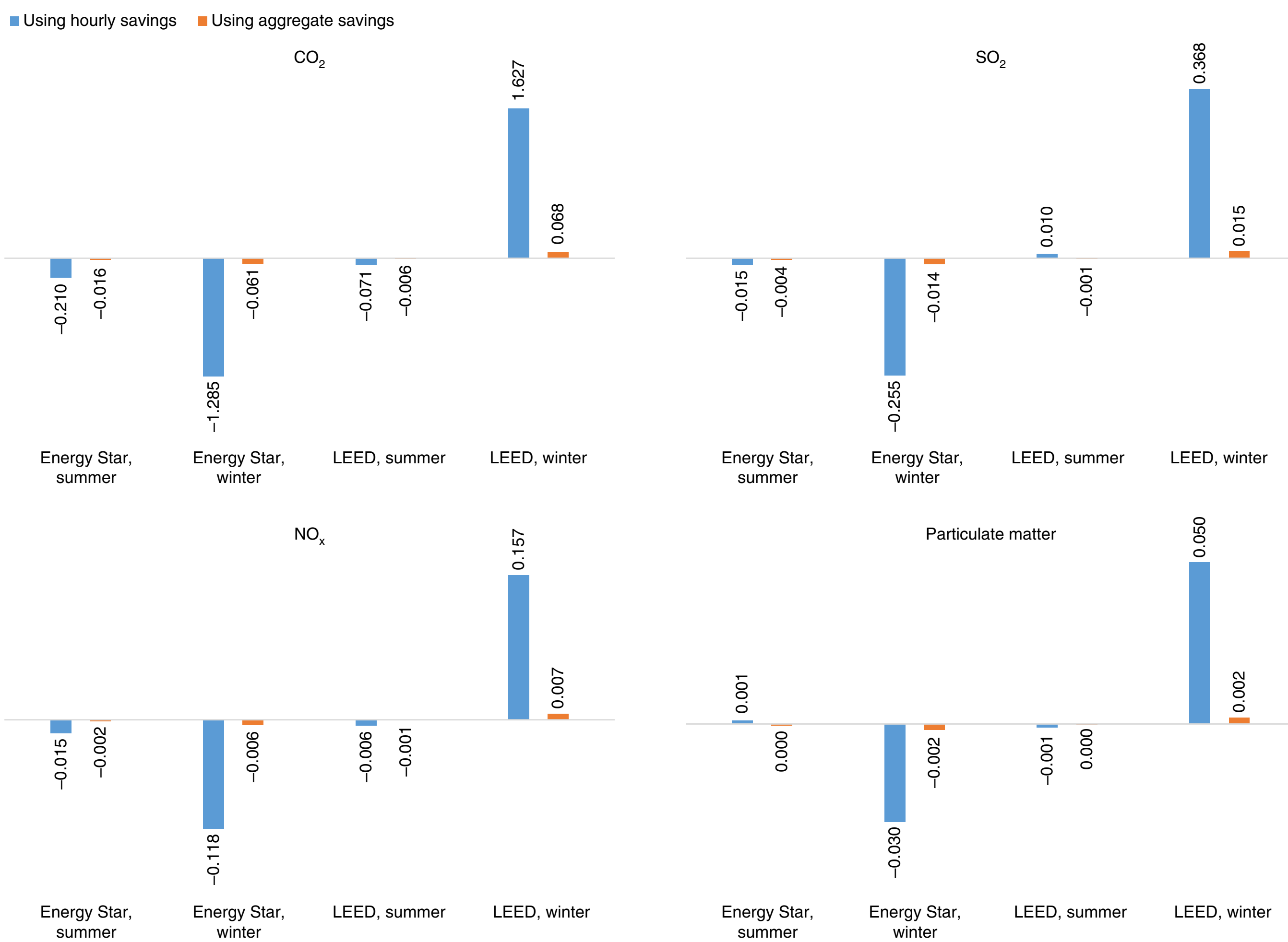

Fig. 3 | Comparison of avoided environmental damages from CO_2, SO_2, NO_x and particulate matter calculated using hourly electricity savings versus aggregate savings. Negative values mean reduced environmental damage, and vice versa. Values are in US$ per customer per day.

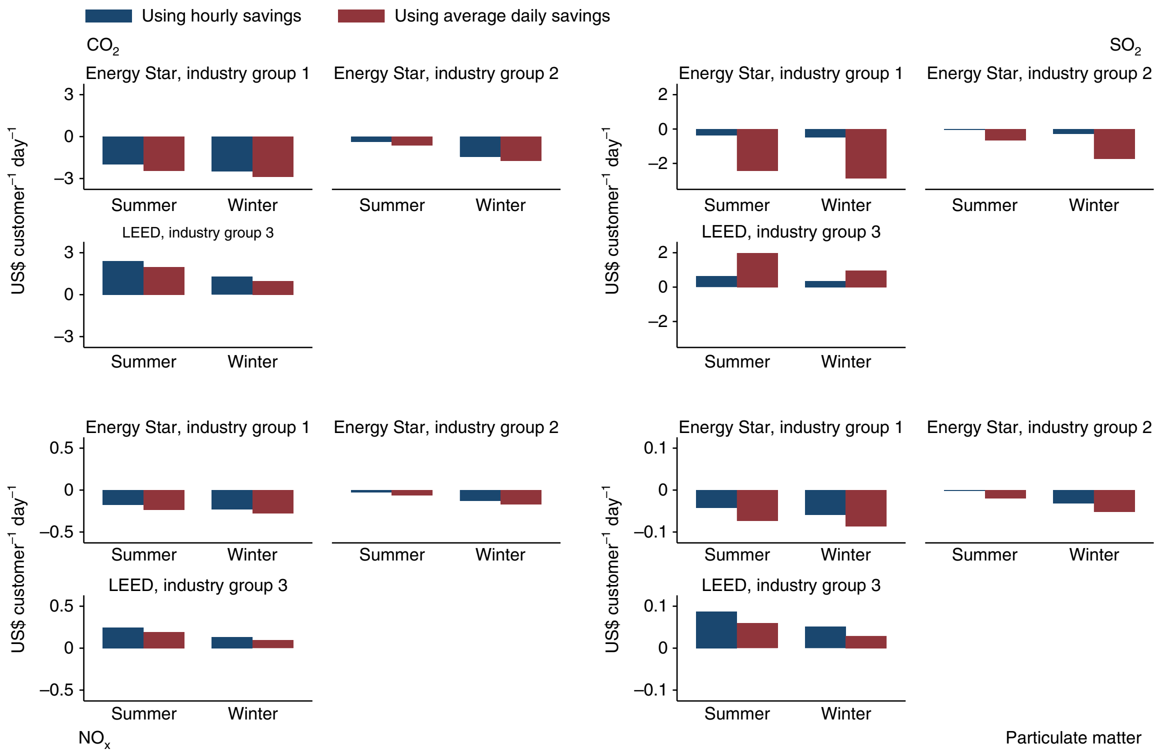

Fig. 4 | Avoided environmental damages by industry type. Industry group 1: 'educational service' or 'health care and social assistance'; industry group 2: 'retail trade'; industry group 3: 'finance and insurance', 'real estate rental and leasing' or 'administrative and support and waste management and remediation services'. Negative values mean reduced environmental damage, and vice versa.

average summer and winter load profiles for both groups to show that the load curves for occupants in green buildings become flatter after certification (see Supplementary Fig. 2).

We estimated the fixed-effects panel regression models 1 and 2 described in the Methods (see Supplementary Tables 5 and 6 for full model results). The coefficients for the interaction terms of Energy Star or LEED certification and hour-of-day indicator report the hourly electricity savings from green certification. We plot these coefficients and their 95% confidence intervals obtained from equation (2) in Fig. 1. These results were obtained after controlling for confounding factors, including price plans, marginal electricity prices, temperature effects and a rich set of fixed effects that control for characteristics at building, occupant, regional and macro levels.

Fig. 1a,b shows that in the summer, Energy Star certification helps building occupants save electricity from 08:00 to 18:00, and the average hourly electricity saving during these hours is 5 kWh h^{-1}. These are exactly the peak and shoulder-peak hours for the utility company in summer months. Furthermore, these occupants use more electricity during some off-peak hours (from 22:00 to 07:00), which makes load curves flatter. For winter months, occupants in Energy Star-certified buildings save the majority of energy from 07:00 to 22:00. Fig. 1c,d shows that for LEED-certified buildings, the majority of summer electricity savings also happen during peak and shoulder-peak hours from 09:00 to 17:00, and the average hourly saving during these hours is 7 kWh h^{-1}. These occupants use more energy between 19:00 and 00:00.

For a larger sample size, we also conducted the matching and econometric analysis including those buildings that obtained green certificates before 2013, giving a total of 128 and 42 accounts for Energy Star and LEED analysis, respectively. The results using the larger sample are similar (see Supplementary Fig. 3).

Our main analysis uses dry-bulb temperature data. Engineering studies show that analyses using wet-bulb temperature data might generate different results[24,25]. As a robustness check, we ran the same regression models using wet-bulb temperature data. We demonstrate that the electricity savings estimated using wet-bulb temperature data are very similar to those estimated using dry-bulb temperature data (see Supplementary Fig. 4 for the key coefficients).

Environmental impact assessment. The hourly impact on electricity consumption enables us to improve the accuracy of environmental impact assessment for green buildings. We conducted an analysis of the carbon and air emissions impact using the marginal damage factors by hour of day (Fig. 2) for North American Electric Reliability Corporation (NREC) regions estimated by Holland et al.[26].

Fig. 3 shows the calculated avoided environmental damage per customer per day, using both the hourly electricity savings and the aggregate savings (the simplified method). A large discrepancy exists for environmental sustainability assessment between using hourly savings versus aggregate savings. The largest avoided damages for Energy Star are from CO_2, followed by SO_2, NO_X and then particulate matter. Our main data are provided by the utility company Salt River Project (SRP). As of 2017, there were 888 business customers located in Energy Star-certified buildings in SRP service territory. Together, these Energy Star business customers are responsible for US$311,479 yr^{-1} of avoided damage from CO_2, SO_2, NO_X and particulate matter (see Methods). Fig. 3 shows that the avoided damages per customer per day from LEED certification are much smaller compared with Energy Star certification. In fact, in the winter, there are actually more damages from LEED certification.

Fig. 3 also shows the differences between the avoided damages calculated using hourly electricity savings (blue columns) and aggregate savings (orange columns). Ignoring the intra-day variation in energy savings can bias the estimation of environmental benefits of green commercial buildings by about 94% for CO_2, 95% for SO_2, 93% for NO_X and 104% for particulate matter. If we use the

Table 1 | Energy bill savings for tenants in Energy Star- and LEED-certified buildings

Price plan		E32		E33		E36	
		Summer	Winter	Summer	Winter	Summer	Winter
Monthly energy bill savings	Energy Star	US$74	US$188	US$56	US$186	US$77	US$214
	LEED	(US$31)	(US$239)	(US$3.5)	(US$231)	(US$29)	(US$239)

Electricity price information

E32:

- May, June, September and October: US$0.1521 kWh^{-1} from 15:00–21:00; US$0.1030 kWh^{-1} from 12:00–15:00 and 21:00–23:00; US$0.0528 kWh^{-1} for all other hours.
- July and August: US$0.1671 kWh^{-1} from 15:00–21:00; US$0.1093 kWh^{-1} from 12:00–15:00 and 21:00–23:00; US$0.0538k kWh^{-1} for all other hours.
- January, February, March, April, November and December: US$0.1151 kWh^{-1} from 06:00–09:00; US$0.1036 kWh^{-1} from 18:00–21:00; US$0.0512 kWh^{-1} for all other hours.

E33:

- May, June, September and October: US$0.2701 kWh^{-1} from 16:00–19:00; US$0.0642 kWh^{-1} for all other hours.
- July and August: US$0.2781 kWh^{-1} from 16:00–19:00; US$0.0643 kWh^{-1} for all other hours.
- January, February, March, April, November and December: US$0.1115 kWh^{-1} from 06:00–08:00; US$0.0644 kWh^{-1} for all other hours.

E36:

- May, June, September and October: average of US$0.0989 kWh^{-1} for all hours.
- July and August: average of US$0.1211 kWh^{-1} for all hours.
- January, February, March, April, November and December: average of US$0.0790 kWh^{-1} for all hours.

Numbers in parentheses indicate energy bill increases rather than savings.

aggregate electricity savings, the Energy Star business customers are only responsible for US$16,848 year^{-1} of avoided damage from CO_2, SO_2, NO_X and particulate matter. Compared with the more precise estimate of US$311,479 yr^{-1}, policymakers and environmental planners could potentially underestimate the environmental sustainability benefit of Energy Star by 95%. The reason for this huge gap is due to the large variation in the types of marginal fuel responsible for electricity generation at different hours of the day.

Environmental impact assessment by industry type. We also examined the impact by industry type. For Energy Star buildings in our sample, there are two major clusters of industry type based on one-digit North American Industry Classification System (NAICS) code: (1) 'educational service' or 'health care and social assistance'; and (2) 'retail trade'. For LEED buildings, most businesses are in the cluster of 'finance and insurance', 'real estate rental and leasing' or 'administrative and support and waste management and remediation services'. We then analysed the hourly electricity savings for these types of industries. For the remaining industries in our sample, including mining, construction and utility companies, and food services, we did not have a large enough sample to generate statistically meaningful results. Hence, we did not conduct the analysis for these other industries. The coefficients for the interaction terms of Energy Star/LEED certification and hour-of-day indicator by industry type measure the change in electricity consumption for each hour of the day (see Supplementary Fig. 5). The results show that for the service industries other than the retail trade, there are electricity savings during the day time and peak hours for both Energy Star and LEED certification—very similar to our main results. In comparison, retail trade with Energy Star certification has smaller hourly electricity savings during the day time. We calculated the avoided damage from environmental pollution for each industry (Fig. 4). In particular, retail trade generated lower environmental benefit from Energy Star and LEED certification than other service industries. Also, the percentage miscalculation of environmental benefit using aggregate electricity savings was higher for the retail trade.

Environmental impact assessment in other regions. To show that our findings can be generalized to a broader geographical context, we used the following simulated data provided by the US Department of Energy Open Data Catalog: the commercial hourly electricity usage profiles for major typical meteorological year (TMY3) locations in major cities of all other US states (except Alaska and Hawaii). We calculated the hourly electricity savings of average commercial buildings for each location for summer and winter months and their associated environmental benefits. From the simulation analysis, we reached three conclusions. First, for other regions in the USA, the majority of electricity savings in summer seasons also happen during peak hours (see Supplementary Fig. 7). Second, traditional methods to assess sustainability that ignore the timing of savings can miscalculate the environmental benefit of green commercial buildings across US states (see Supplementary Figs. 8–11). The exact amount of miscalculation depends on the load profile and hourly marginal pollution damages for a specific location. Third, based on the simulation results from other regions, we demonstrate that our main conclusions can be generalized. We also further illustrate the importance of using high-frequency electricity data to improve the precision of sustainability assessment.

Economic impact results. Based on the electricity rate information of SRP and the estimated savings by hour of day, we calculated the energy bill savings of customers in green-certified commercial buildings. The results are listed in Table 1. Since time-of-use electricity rates have electricity prices that vary by hour of day, estimated savings at the hourly level can enable more precise evaluations of bill savings. The annual bill savings for a business tenant in an Energy Star-certified building range from US$1,452 to US$1,746, depending on which price plan the tenant is on. This is equal to about 2% bill savings based on the average annual electricity bills of commercial customers. For tenants in LEED-certified buildings, there are bill increases, especially during winter, due to the fact that there are energy consumption increases in winter peak hours when heating is needed and the electricity price is high.

There are also other real benefits for users from green-certified buildings. Studies show that green buildings have improved thermal comfort[27], improved indoor air quality and lighting[28], can improve occupant productivity and organizational success[29], and may positively affect public health[30]. Green buildings are shown to play an important role in mitigating climate change due to their location in dense urban areas and access to employment and services[31]. The impact of climate change is exacerbated in urban areas due to its distinctive biophysical features, such as less vegetated surfaces and the urban heat island effect[32]. Thus, green urban infrastructure including green buildings is critical to provide comfortable living environments and, meanwhile, reduce carbon emissions.

There are three potential economic benefits for electricity utility companies. First, because of usage shift from peak hours to off-peak hours, they can save on their cost of providing electricity by selling more electricity at a lower marginal cost and less electricity at a higher marginal cost. Second, reducing peak-hour electricity consumption can help utility companies maintain the stability of their grid by avoiding blackouts during peak hours. Lastly, in the long run, reducing peak-hour electricity consumption can help utility companies delay expensive capital investment in peaking power plants—the capacity values[18,19]. We estimate that, on average, for each business tenant located in an Energy Star building, utility companies can save US$1,537 annually by selling more electricity at a lower cost in off-peak hours and less electricity at a higher cost in peak hours (see Methods). For a business tenant located in a LEED building, utility companies can save about US$300 annually.

In terms of delaying the capital cost of peaking power plants, we use the capital cost of power plants to estimate such economic value. According to the US Energy Information Administration[33], the overnight capital cost of a combined-cycle natural gas power plant is about US$978 kW^{-1}. Our results show that during summer peak hours at around 16:00, a business tenant located in an Energy Star or LEED building can reduce energy consumption by 6–8 $kWh\,h^{-1}$, which is equal to a reduction of generating capacity of 6–8 kW. This is equivalent to a delay of US$6,846 investment cost per customer (see Methods for an alternative way to calculate capacity values).

Discussion

This study uses previously unavailable high-frequency electricity consumption data to improve sustainability assessment of green buildings. Given that electricity savings are uneven throughout the day, policymakers should adopt more sophisticated methods to accurately examine the environmental benefit of green buildings, taking into consideration the variation in marginal emission factors during the day. Average emission factors aggregated at daily, monthly or yearly levels should be avoided in evaluating the environmental benefits of energy efficiency, because the mix of fuel for electricity generation differs by time of day and can yield misleading results.

The estimated electricity savings in this paper are the net of any electricity consumption behavioural changes. A main behavioural factor is the 'rebound effect'—the actual energy savings of energy efficiency upgrades are lower than theoretical savings[34–37]. Our study contributes to the literature on rebound effects by showing that the magnitudes of rebound effects could potentially differ by hour of the day as well. Overall, rebound effects from LEED certification are larger than those from Energy Star certification.

In terms of economic benefits, traditionally, without regulatory mandates, utility companies do not have incentives to encourage energy efficiency because it reduces their revenue from selling electricity. Our results show that energy efficiency through green certification of commercial buildings can potentially give utility companies economic benefits by reducing peak hour demands, and hence reducing costs by lowering the idle capacity. Currently, in addition to energy-efficiency-related rebates aiming to reduce overall energy consumption regardless of intra-day timing, utility companies have also implemented incentives to encourage their customers to participate in demand-side management, which focuses on reducing peak demand. Our finding that green-certified commercial buildings can help reduce peak-hour electricity demand should encourage utility companies to provide incentives of green certification to commercial consumers.

Methods

Data. Electricity consumption data of individual commercial electricity customers were obtained through SRP—a major utility company in the Phoenix metropolitan area. The dataset contains account-level hourly interval electricity demand data for 2013–2016. The dataset also includes information such as monthly electricity pricing plans, customer locations and industry codes. For commercial customers, there are three electricity pricing plans: the E32 time-of-use (TOU) general service plan; E33 TOU experimental plan; and E36 standard general service plan. E32 has higher energy prices during peak hours (for example, 14:00–19:00 in the summer) and lower energy prices during off-peak hours. E33 has shorter peak hours from 16:00–19:00 and higher peak-hour prices than E32. E36 has a decreasing block rate, meaning that the marginal energy prices decrease when customers consume more energy and the prices do not differ by time of day.

We also collected LEED and Energy Star certification data from the US Green Building Council and Environmental Protection Agency websites. This dataset includes rich information on all green-certified commercial buildings in the Phoenix metropolitan area. For Energy Star, this dataset contains building names, industry types, building owners, property managers, addresses, Energy Star ratings, Energy Star label years, floor spaces and years built. For LEED, this dataset contains project names, addresses, LEED system versions, LEED points achieved, certification levels, registration dates, certification dates, owner types, floor spaces and project types. We matched the addresses from the LEED and Energy Star database to the SRP database to identify the commercial electricity accounts located in green-certified commercial buildings.

We obtained the hourly temperature data, including both dry-bulb and wet-bulb temperatures, for each electricity customer from National Oceanic and Atmospheric Administration (NOAA) Climate Data Online (https://www.ncdc.noaa.gov/cdo-web/). NOAA provides hourly historical temperature data for all US weather stations. Based on the addresses of electricity customers, we matched each customer with the nearest weather station. Then, based on the temperature data, we calculated cooling degree days and heating degree days on a 65° threshold.

Empirical strategy. *Matching method.* Both LEED and Energy Star programmes are voluntary, which can lead to selection bias. For example, more energy-savvy or environmental-conscious occupants might be more likely to choose to locate in a green building. In addition, potential omitted variable issues can also cause endogeneity. Examples of these confounding factors include building codes[38], changes of building occupancy, and changes of electricity pricing plans, which can influence both the selection of green certification and energy consumption.

In this study, we used a combination of matching and difference-in-differences approaches to address the potential endogeneity issues, following the approach by Fowlie et al.[23]. Although existing post-occupancy evaluation analyses of green buildings also adopt matching methods[6,39], the key challenge is to find the comparable control group. Limited by data availability, existing studies usually do not have the energy consumption data of similar buildings located in the same district as the green buildings in their sample. Instead, existing studies use commercial buildings with similar characteristics in the same census division found in the Energy Information Administration's Commercial Buildings Energy Consumption Survey as their control groups. This matching process is coarse because key characteristics that can dramatically affect energy consumption are omitted (for example, building occupant types and electricity pricing plans). In addition, the weather conditions within a census division can vary significantly. This study significantly improves the quality of the matched control group using an advanced matching algorithm, the accuracy of which is improved by the much better availability of closely approximated matches.

Our primary analysis is at the electricity account level, instead of at the building level. A commercial building could have multiple electricity accounts or occupant units. We chose this unit of analysis to control for changes of occupancy characteristics within a commercial building and sorting of building occupants into different types of buildings. In addition, in our main analysis, we chose to analyse electricity accounts located in green-certified buildings that have both pre- and post-certification high-frequency electricity consumption data to enable difference-in-differences analysis. In other words, these green building tenants went through the certification process during 2013–2016. We analysed LEED and Energy Star buildings separately.

We used the single-nearest-neighbour method to match on the Euclidian-type distance based on two observed attributes: the average pre-certification summer load profile and average pre-certification winter load profile. For every customer located in a green-certified commercial building (that is, each treatment customer), we found a control customer with the same North American Industry Classification System code, located in the same zip code but not located in a green-certified building, and with the most similar summer and winter electricity load profiles before the treatment. To match on electricity load profiles, we calculated the Euclidian-type distance using the average energy consumption (kWh) of every hour of the day for summer and winter.

Balancing statistics between the treatment and control groups in the pre-certification period were also checked to ensure comparability. To test the sample equivalence, we used the standardized mean difference (SMD) for sample means and variance ratios for distribution[40]. For a given attribute Y_j, the SMD was defined as $\mathrm{SMD}_j = \frac{|\mathrm{Y}'_{j\mathrm{T}} - \mathrm{Y}'_{j\mathrm{C}}|}{\sqrt{((\mathrm{s.d.}_{j\mathrm{T}})^2 + (\mathrm{s.d.}_{j\mathrm{C}})^2)/2}}$, where the subscripts T and C indicate treatment and control groups, respectively. The variance ratio was defined as $\mathrm{VR}_j = \frac{(\mathrm{s.d.}_{j\mathrm{T}})^2}{(\mathrm{s.d.}_{j\mathrm{C}})^2}$. Rubin[41] suggests that if the SMD is greater than 0.25, or the variance ratio falls outside of the range between 0.5 and 2, the two groups are not balanced in means and distribution. We calculated the balancing statistics for hourly energy consumption to ensure matching on electricity load profiles.

Econometric model. The key purpose of this study was to examine the timing of electricity savings. To do so, we used smart meter data, which only became available in Arizona in late 2013. The timing and absolute amount of savings are important from an electric load management perspective, and for evaluating the economic and environmental benefits of green buildings. Thus, in this analysis, instead of using natural logs of energy consumption, we used the absolute amount of energy demand as the dependent variable, following Boomhower and Davis[18]. We ran the following panel regressions:

$$kWh_{it} = \sum \varphi_h \times_{it} \times \text{hour of day}_{it}^{h} + \lambda P_{it} + \sum \gamma_r P_{it} \times R_{it} + \sum \rho_r \times R_{it} + \theta' \times f(W||it) + \eta_i + \mu_y + \varphi_m + \xi_d + \omega_h + \varepsilon_{ih} \quad (1)$$

where i denotes the individual account, t indicates the hour of the sample, $_{it}$ is an indicator variable equal to 1 if a building is green-certified in hour $_t$ of the sample, hour of day$_{it}^{h}$ is the indicator variable of hour of day and there are 24 such dummy variables, P_{it} is the marginal electricity price faced by account i at time t, R_{it} is the electricity pricing plan faced by account i at time t, $f(W||it)$ is the cooling degree day and heating degree day spline, n_i represents individual account fixed effects that can control for unobservable confounding factors such as building occupant characteristics and the duration (time length of recorded energy consumption data) of each building occupant in our dataset, μ_y is the year-of-sample fixed effect, which can control for annual changes that can impact building energy consumption such as macroeconomic and policy conditions, φ_m is the month-of-year fixed effect, ξ_d is the day-of-month fixed effect and ω_h is the hour-of-day fixed effect. There are 24 coefficients φ_h, which measure the electricity savings of green-certified buildings by hour of day. We also ran the following model specification with day-of-sample fixed effects ρ_{ds}, which required more computational resources to run but could control for more time-variant unobservables at the daily level:

$$\mathrm{kWh}_{ih} = \sum \varphi_h \times_{it} \times \text{hour of day}_{it}^{h} + \lambda P_{it} + \sum \gamma_r P_{it} \times R_{it} + \sum \rho_r \times R_{it} + \theta' \times f(W||it) + \eta_i + \rho_{ds} + \omega_h + \varepsilon_{ih} \quad (2)$$

Environmental impact assessment. The hourly impact on electricity consumption enables us to improve the accuracy of environmental impact assessments for green buildings. We conducted an analysis of the carbon and air emissions impacts using the marginal damage factors by hour of day for NREC regions estimated by Holland et al.[26]. Arizona is located in the Western Electricity Coordinating Council (WECC) region, so we used the average hourly marginal damage factors for the WECC. Following Holland et al.[26], we assumed that a unit of electricity savings at any building within a given NERC region had the same marginal emissions factors as a unit of electricity savings at any other building located in the same NERC region. We analysed CO_2, SO_2, NO_X and particulate matter, which are the major pollutants from electricity production. The marginal damages were lower during the day and higher during the night, due to marginal electricity-generating units being cleaner during peak hours during the day.

We calculated the daily avoided damages for each business customer from CO_2, SO_2, NO_X and particulate matter using $\sum_h \mathrm{MD}_h\varphi_h$, where h indicates the hour of the day, MD_h represents the marginal damages per kWh from each of the pollutants for hour h, and φ_h is the electricity savings (kWh) for hour h obtained from equation (2). $\mathrm{MD}_h\varphi_h$ is the avoided damage for hour h. To obtain daily avoided damages, we summed the hourly avoided damages across all hours, $\sum_h \mathrm{MD}_h\varphi_h$. In the absence of hourly electricity savings, researchers can apply a 'simplified' method of using aggregate average daily electricity savings and average marginal damage factors to calculate the avoided damages per customer per day. We calculated this 'simplified' avoided damage using $\frac{\sum \mathrm{MD}_p}{24}\sum \varphi_p$, where $\frac{\sum \mathrm{MD}_p}{24}$ is the average marginal damage factor (in US\$ kWh^{-1}) across all hours of the day and $\sum \varphi_p$ represents the average daily electricity savings calculated by adding up the hourly savings.

After obtaining daily avoided damage from environmental pollution for each business customer, we calculated the annual avoided environmental damage for all business customers located in an Energy Star-certified building under SRP's service territory. The annual total benefits were calculated by multiplying the avoided damage (per customer per day) by the number of Energy Star customers and the number of days for each season. As of 2017, there were 888 business customers located in Energy Star-certified buildings in SRP's service territory. From Fig. 3, we know that the avoided damage from CO_2 is US\$0.21 customer^{-1} day^{-1} for summer months and US\$1.28 customer^{-1} day^{-1} for winter months; the avoided damage from SO_2 is US\$0.015 customer^{-1} day^{-1} for summer months and US\$0.255 customer^{-1} day^{-1} for winter months; the avoided damage from NO_x is US\$0.015 customer^{-1} day^{-1} for summer months and US\$0.118 customer^{-1} day^{-1} for winter months; and the avoided damage from particulate matter is −US\$0.001 customer^{-1} day^{-1} for summer months and US\$0.03 customer^{-1} day^{-1} for winter months. The total avoided damage from all four types of pollution for summer months per customer is therefore $(0.210+0.015+0.015-0.001)\times 365/2$, where 365/2 is used to calculate the number of days for summer months; and the total avoided damage from all four types of pollution for winter months per customer is $(1.28+0.255+0.118+0.03)\times 365/2$. Adding avoided damages for winter and summer months together for each customer and multiplying by the total number of Energy Star business customers, we get $((0.210+0.015+0.015-0.001)\times 365/2+(1.28+0.255+0.118+0.03)\times 365/2)\times 888=$ US\$311,479 yr^{-1}. Thus, together, these Energy Star business customers are responsible for US\$311,479 yr^{-1} of avoided damage from CO_2, SO_2, NO_X and particulate matter.

Simulation analysis for other states. To prove that our findings can be drawn to a broader geographical context, we conducted the following four-step simulation analysis for other US continental states.

1. We obtained the average summer and winter month load profiles for commercial buildings in a major city of each state. The data were obtained from the US Department of Energy Open Data Catalog (https://openei.org/doe-opendata/dataset/commercial-and-residential-hourly-load-profiles-for-all-tmy3-locations-in-the-united-states), which contains hourly load profiles for 16 commercial building types. We calculated the average load profile across all building types. We then plotted the summer and winter commercial building load profiles for each location across the USA (see Supplementary Fig. 6).
2. Then, using the coefficients that measure the hourly electricity savings from Energy Star and LEED certification, as well as the pre-certification hourly electricity consumption information, we calculated the percentage change in electricity savings for each hour from Energy Star and LEED certification.
3. Next, using the percentage savings obtained from step (2) and the hourly load profile in step (1), we calculated the hourly electricity savings due to Energy Star and LEED certification for each location. We then plotted the hourly savings for each state (see Supplementary Fig. 7). Positive values indicate an increase in electricity consumption while negative values indicate a decrease in electricity consumption.
4. Lastly, we obtained the average hourly marginal damages (US\$ kWh^{-1}) from CO_2, SO_2, NO_X and particulate matter in each of the NREC regions. We merged each location with its corresponding NREC region. Then, we multiplied the hourly savings with the hourly marginal damages to calculate the avoided damages from these environmental pollutants due to Energy Star and LEED certification. As a comparison, we also report the avoided damage using aggregate electricity savings. We plotted the avoided per-customer daily damages from each of the pollutants for each state (see Supplementary Figs. 8–11).

Calculating savings for utility companies using wholesale electricity prices. To quantify the impact for electricity utility companies, hourly wholesale electricity price data were needed. However, such information is not public and is hard to obtain from utility companies. We borrowed the hourly wholesale electricity prices of California (a neighbouring state of Arizona), as reported in Boomhower and Davis[18]. Then, we calculated the estimated daily cost savings per business customer based on the hourly wholesale electricity prices and our estimated savings by hour of day using $\sum_h \wp_h\varphi_h$. Here, $\wp_h$ is the wholesale electricity price for hour h, and φ_h is the electricity savings (kWh) for hour h obtained from equation (2).

An alternative method to calculate the value from reducing capacity cost. We also used another method to calculate the value of capacity cost reduction. We used the average monthly contact price of US\$2.66 month^{-1} for capacity from California's Resources Adequacy Program[42] from 2013–2014 as a proxy for capacity value in Arizona. Because the system peak load reduction estimated from our study is 6–8 kW (using 7 kW as a midpoint), this is equivalent to US\$2.66 × 7 × 12 = US\$223.4 year^{-1} customer^{-1}. Assuming a 20-year lifetime of a power plant and 5% interest rate, this yearly value is then equal to US\$2,785 per customer. This estimate is on the same order of magnitude as that obtained from using investment costs for power plants.

Data availability

The weather data are available from NOAA at https://www.ncdc.noaa.gov/cdo-web/. The Energy Star data are available from https://www.energystar.gov/index.cfm?fuseaction=labeled_buildings.locator. The LEED data are available from https://www.usgbc.org/projects. The high-frequency electricity data that support the findings of this study are available from the SRP, but restrictions apply to their availability. These data were used under a non-disclosure agreement in the current study, and so are not publicly available. However, they are available from the authors upon reasonable request and with permission from the SRP.

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Author contributions

Y.Q. secured project funding, collected and cleaned the data, and conducted the statistical modelling. Y.Q. and M.E.K. designed the study, analysed the data and wrote the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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