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Utilities Included: Split Incentives in Commercial

Electricity Contracts

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Abstract

The largest decile of commercial electricity customers comprises half of commercial sector electricity usage. We quantify that a substantial split incentives problem exists when these large firms are on electricity-included property lease contracts. Using exogenous variation in weather shocks, we show that customers on tenant-paid contracts use 6-14% less electricity in summer months. The policy implications are promising. Nationwide energy savings from aligning incentives for the largest 10% of commercial customers exceeds the savings from doing so for the entire residential electricity sector. It is also cost-effective: switching to tenant-paid contracts via sub-metering has a private payoff period of under one year.

JEL: D22, L14, Q41, Q51
Keywords: Electricity; Principal-Agent Problem; Contracts.

1. Introduction

In this paper we identify the alignment of landlord and tenant incentives as an opportunity for cost-effective pollution abatement. A principal agent problem arises because of the separation between those who pay for energy usage and those who make decisions about durable investments or consumption, leading to potential welfare losses from excess energy use that even Pigouvian taxes are not well suited to correct (Jaffe and Stavins (1994), Gillingham and Palmer (2014)). The welfare costs may be particularly substantial in the commercial sector since these users account for over 35 percent of end-use electricity consumption in the U.S., and about half of these units are occupied by renters. Regulators and industry alike recognize the potential energy savings from tenant-paid utilities contracts, and have advocated for and incorporated policies that would facilitate these contract types (NRDC (2011), IBE (2011), ASHRAE (2012), USGBC (2009), USGBC (2013)), yet little direct evidence exists in the commercial sector.

The possibility that misaligned incentives between a principal and an agent can cause inefficiencies has been raised in many settings, including the design of employment, credit, insurance and agricultural contracts (Stiglitz (1974), Grossman (1983), Chiappori and Salanie (2000), Goodwin (2001), Finkelstein and McGarry (2006), Karlan and Zinman (2009), Einav et al. (2013)). Energy economists have also weighed in on this question by testing for principal agent problems in the residential energy space (Levinson and Niemann (2004), Gillingham et al. (2012), Elinder et al. (2017)). In this setting a frequently studied split incentive principal agent problem takes the form of a tenant paid contract and underinvestment in energy efficiency by the landlord. The logic, and one that has been corroborated by empirical work, is that if tenants are not able to perfectly observe efficiency levels and

are thus unwilling to pay a rent premium for energy efficiency, owners may forgo net beneficial energy conservation investments (Davis (2012), Myers (2014)). Our focus is on split incentive problems created when energy bills are bundled into the monthly rental contract. When a building occupant rents space and does not pay for their monthly energy bill, they face a zero marginal cost for energy use, resulting in little incentive to consider the impact of their energy consumption decisions.

Growing evidence points to modest energy savings from the introduction of tenant-paid contracts for residential customers, but the literature has remained relatively silent on the topic of commercial usage. The sparsity of empirical work in this setting may be partly explained by the difficulty of disentangling the effect of split incentives from sorting by either tenants or landlords on the basis of energy characteristics (Kahn et al. (2014)). Understanding the split incentive problem for commercial customers is important since relative to their residential counterparts they are large in size but few in number, and may offer an opportunity to achieve energy conservation at a lower cost. This paper aims to fill this gap by taking advantage of a unique empirical setting and rich data to test for the effect of split incentives in the commercial sector, as well as explore heterogeneity in response to contract type.

Our empirical approach uses variability in billing periods across firms to generate exogenous differences in local weather within a calendar month. Local weather is measured as the number of cooling degree days and heating degree days within a given zip code and billing month. We combine these data with monthly billing data from 1,126 firms serviced by a Connecticut electric utility between October 2007 and May 2011, and property-level information on fixed observables including whether the tenant or landlord pays the electric bill (we refer to this as "contract type" throughout the manuscript). Endowed with panel data on both weather and

usage, we then examine the differential impact of a local weather shock on electricity usage across tenant-paid versus owner-paid contract types, controlling for aggregate time shocks and firm fixed effects.

To interpret our results as the causal effect of contract type on electricity usage changes, we address two primary identification challenges. First, we establish a common basis of comparison - a response gradient to a stimulus that influences demand for electricity and that is exogenously experienced by firms of both contract types. We use weather exposure within a given billing-cycle zip code as the exogenous electricity demand shifter. While firms in our sample are located within a relatively small geographic region, their billing cycles are substantially non-overlapping. Variation in temperature across days means that firms in different billing cycles will experience different temperature exposure based on the start- and end-dates of their billing month. The differential temperature exposure allows us to compare the electricity-temperature response gradient across firms that pay for their electricity and those that do not.

Second, we address concerns that firms may select into contract type based on unobservable characteristics that are correlated with the response gradient. Firms with elastic electricity demand may be more inclined to select a tenant-pays rental contract than those with inelastic demand. Ultimately, causal interpretation of our results relies on an assumption that there is no such selection on unobservable firm characteristics. We present three pieces of empirical evidence in support of this assumption. First, we show that contract type is not systematically correlated with a rich set of observable characteristics. If firms were strategically selecting into contract type, we would expect to see low-demand (high-demand) firms selecting into tenant-pay (owner-pay) contracts. We do not, and it is therefore unlikely that they are self-selecting based on response gradient, a second-order attribute. Second,

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we exploit a change to an important energy metering regulation in Connecticut that altered building owners' ability to select utility contract types in their buildings. This change provides us an opportunity to test if *changes* in contract choice at the building level are correlated with firm-level energy consumption characteristics. We find that they are not. Further we show that 'switchers', or firms located in buildings whose owners chose to select different contracts after the regulatory change, do not exhibit differential responses to the temperature gradient relative to the other firms in the sample. Third, we assess the effect of potential correlations between any remaining unobservable characteristics and the treatment, as described in Oster (2016), to identify bounds on our treatment effect. The bounds implied by this technique provide evidence that our conclusion is robust to such concerns. Collectively, these tests support the assumption that differential sorting in response to the temperature gradient is unlikely to confound the relationship between contract type and electricity usage in our setting.

Our main result suggests that among the largest consumption firms, tenant-paid contracts induce substantial energy savings. For the top decile of electricity users switching from an owner-paid to tenant-paid utilities contract would reduce electricity usage by about 1.4 percent per average daily cooling degree day. Over the course of the year, the electricity savings from a tenant-paid contract among top users amounts to roughly 3 percent, and in the summer months up to a 13 percent. The coefficient bounds analysis proposed by Oster (2016) yields a lower bound on savings of 0.7 percent per cooling degree day. Interestingly, for the other 90 percent of commercial customers contract type does not impact consumption decisions. This behavior is consistent with a setting in which the benefits from changing consumption, in the form of bill savings, do not cover the adjustment costs for small firms.

Given the size of the responsive firms, the estimated treatment effect translates into significant private and public benefits (or costs) from the choice of contract type. Using the Oster bounds, the private average annual utility bill savings from a tenant-paid utilities contract among high usage firms is between 1.3-2.5 percent. These effects are large when aggregated. The private savings per firm are almost fifteen times larger than the private household savings attributable to building energy codes, and over fifty times larger than the private savings from tenant-paid heating in apartment buildings in the northeastern US (Jacobsen and Kotchen (2013), Levinson and Niemann (2004)). Were incentives to be aligned among all large commercial firms nationwide, total energy saving would exceed those produced by solving the split incentives problem for the entire residential electricity sector. Environmentally, our estimates imply greenhouse gas savings of between 615-1200 thousand tons of CO_2 per year, or roughly 3.3 to 6.6 times the average annual savings achieved from Weatherization Assistance Program retrofits performed in a given year. These savings come at a relatively low cost - retrofitting units with sub-meters to allow switching to tenant-paid utility bills amongst the highest decile of electricity users has a payback period of less than one year.

Our work makes three contributions to the current dialogue on the design and implementation of energy conservation programs, and may help guide policymakers in their efforts to conserve energy and combat climate change. First, relative to the residential setting where a growing literature points to the potential and limitations of energy conservation and efficiency programs (Gillingham et al. (2012), Hassett and Metcalf (1999), Fowlie et al. (2015)), little is known about the transferability of these instruments to commercial users. We provide a well identified counterpart to existing residential estimates on the split incentives problem. Second, our results reveal substantial heterogeneity in firm responsiveness to contract type and point

to the importance of looking beyond average treatment effects. The targeting of contract restructuring based on a readily available observable (firm size) could yield energy savings and cost effectiveness comparable to oft-deployed behavioral energy conservation tools (Allcott (2011), Allcott and Mullainathan (2010)). Lastly, our results suggest that a targeted prescriptive policy of tenant-paid contracts would be a net beneficial addition to the portfolio of greenhouse gas abatement strategies utilized by policymakers.

The rest of the paper is organized as follows. Section 2 discusses past literature and our empirical setting. Section 3 describes the data used in our analysis. Section 4 presents our empirical specification. Section 5 discusses our identification strategy. Section 6 describes our empirical results, presents our external and aggregate benefit estimates, and provides further context by discussing the private net benefits of energy conservation in the commercial sector. Section 7 concludes.

2. Background

Separating the party who pays for energy from the one making decisions about usage has been frequently cited as creating incentives for energy over-consumption (Prindle et al. (2007), Murtishaw and Sathaye (2006), Blumstein et al. (1980)). Given that about 50 percent of office and retails buildings are tenanted, or non-owner-occupied, the commercial sector has the potential to be a primary contributor to this agency problem (EIA (2012)). However, this is also the sector for which the least empirical evidence exists on the magnitude of the problem.

In the commercial and industrial sector, a reduction in the incentive to conserve may lead to energy overconsumption along multiple dimensions. One end use that can be affected is air conditioning. Many buildings are over-cooled in the summer months, leading to an increase in commercial electricity consumption of up to 8

percent (Derrible and Reeder (2015)). Office equipment and miscellaneous electronics usage may also increase if there are poor incentives to conserve. Sanchez et al. (2007) find that office equipment and miscellaneous equipment such as computers, personal space heaters and fans account for up to 20 percent of annual electricity consumption in the commercial sector. In retail settings, keeping doors open in the summer months may also increase consumption by up to 9 percent (Basarir (2010)). Finally, there may simply be inattention to electricity decisions in the commercial customer population. This explanation is consistent with Jessoe and Rapson (2015), who show that commercial customers are price inelastic when exposed to time-varying electricity prices.

While the engineering literature has identified several channels through which split incentives may affect commercial sector consumption, a gap remains in our understanding of its precise magnitude. One exception is Kahn et al. (2014). This study notes that energy consumption by tenants who pay their own energy bills is 20 percent lower compared to owner-paid units, though this estimate reflects the effect of both contract type and sorting into buildings based on preferences for energy use. In the residential sector, the consensus thus far is that the split incentive effect on aggregate consumption is likely modest. Levinson and Niemann (2004) find that energy bills are 1.7 percent higher when apartment dwellers do not pay for heat, and Gillingham et al. (2012) find occupants who pay for heating are 16 percent more likely to change their heat settings at night.[1] Note that aligning financial incentives does not a priori guarantee that agents will exhibit price-sensitivity in their decisions. In the residential electricity setting, consumers have been shown to be inattentive

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[1]Another dimension to the principal agent problem is less than efficient turnover from oil-fired to gas-fired boilers used for residential heating in the northeastern U.S (Myers (2014)). This outcome is consistent with tenant asymmetric information about heating costs when they pay for heat. Myers (2014) finds that this led to 37 percent higher annual heating costs in the 1990-2009 period, which is a considerable effect.

to their electricity bills (see, for example, Jessoe et al. (2014)). This is potentially a result of the relatively small financial rewards at stake. Casual observers of the commercial space may conjecture that the profit motive and higher usage levels will lead to more attention and also a larger split incentives problem, and one would expect that to be true in the absence of adjustment costs.

The regulations surrounding metering in Connecticut make it an advantageous setting in which to study the split incentives problem. To get a sense for the regulatory landscape, consider the owner of a multi-tenanted building. Monitoring each tenants individual electricity usage would require the installation of a sub-meter. However, prior to the summer of 2013 the state prohibited the retrofitting of commercial and multi-family buildings with sub-meters. As a result, only buildings constructed with sub-meters could charge individual tenants for energy consumption. In all other buildings electricity consumption was monitored at the building level, and thus tenants signed landlord-pay contracts. Since our analysis focuses on the time period 2007 to 2011, the presence of sub-meters in buildings is predetermined from the perspective of current owners and tenants. While tenants are still able to choose buildings based on electricity contract type, doing so limits their choice set to sub-metered buildings, an implicit cost.

In 2013, new legislation passed by the Connecticut General Assembly eliminated this prohibition (Hartford Business Journal (2013), Murtha Cullina LLC (2013)). While we cannot directly test the effect of this change on electricity use, the legislative change enables us to gain further insights into selection on contract type based on firm and building-level energy preferences. We obtain data on contract "switchers" in the post-2013 period, where switchers are defined as firms located in buildings that changed their contract type from owner-paid to tenant-paid utilities, or vice versa. Altogether 65 firms were located in one of these buildings.

We evaluate our research questions within the jurisdiction of United Illuminating (UI), an investor owned electric utility in Connecticut that services customers in 17 Connecticut counties. Figure 1 shows its service territory. Most UI customers heat their homes with natural gas or fuel oil rather than electricity (EIA (2016)), leading us to hypothesize that electricity use will be most responsive to weather conditions in the summer months, when air-conditioning use is high.

3 Data

We combine three data sets to form a panel of of 40,962 observations from 1,126 firms that we use in our analysis. The first data set is monthly billing data provided by UI that reports account-level electricity consumption (in kWh), peak monthly throughput (in kW), and expenditure. These data also contain information on the industrial classification number, or NAICS code of each account. The second source is the CoStar Group, a commercial sector multiple listing service and database that includes property-level information on utility contracts and hedonic characteristics such as building size, stories and year of construction. Third, we obtained daily temperature data from the National Oceanic and Atmospheric Administration (NOAA).

Table 1 identifies the property types that make up our sample. The predominant share of accounts are located in office buildings (72 percent), followed by industrial buildings (22 percent), then by retail and flex buildings, which combine office and retail functions (6 percent). Table 2 presents sample summary statistics on usage, location and industry by contract type. In our sample, about 84% of firms pay their own electricity bill. The average customer (across contract types) spends about \$675 a month on electricity, the average building is approximately three stories, and the primary industry is 'Finance, Real Estate and Management', which makes up about 50 percent of the sample among both contract types. The sample in both contract

types is also evenly regionally distributed, with about 30 percent of observations in central cities, and the rest located in more suburban areas.[2]

3.1   Weather

In our study, weather is measured as the number of cooling degree days and heating degree days in a zip code billing-month. To arrive at this observational unit, we begin by using daily temperature data collected from ten local weather stations to construct daily cooling degree days (CDD) and heating degree days (HDD) at each weather station. CDD are obtained by subtracting 65 from the average Fahrenheit temperature on a given day with temperatures above 65 and HDD are obtained by subtracting the average Fahrenheit temperature on a given day from 65 on days with temperatures below 65.[3] These daily weather station measures are used to compute daily zip code level weather using inverse distance weighting, and are then summed across billing-month in each zip code to obtain monthly CDD and HDD. Finally, for ease of coefficient interpretation, we divide cumulative CDD and HDD in each billing period by total days in that (roughly monthly) billing period to arrive at average daily CDD and HDD.

This observational unit provides both cross-sectional and temporal variation in weather. One source of cross-sectional variation arises from temperature differences across the 32 zip codes in UI's service territory. This is made clear in Figure 2 which

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[2]The last column of Table 2 presents the normalized difference, which is measured as the difference in averages for each variable, by treatment status, scaled by the square root of the sum of the variances. Mathematically, the formula for the normalized difference is $\frac{\bar{X}_1 - \bar{X}_0}{\sqrt{S_1^2 + S_0^2}}$, where $\bar{X}_i$ denotes the mean of a given covariate by utility contract status $i = 0, 1$, and S_i^2 denotes the sample variance of X_i. The normalized difference is preferable as a measure of overlap than a t-test, since this latter measure depends on the sample size, whereas overlap in any given sample is a concept independent of sample size (Imbens and Wooldridge (2009)).

[3]CDD measure demand for space cooling services such as air conditioning since as temperature rises above 65 cooling demand increases. HDD measure demand for space heating services since heating demand increases as temperature falls under 65.

displays the daily temperature by zip code between October 2007 and May 2011. Despite the relatively small region, there is visible cross-sectional variation in daily temperatures with summer temperatures varying between 5 to 10 degrees across zip codes. Variation in weather also occurs because of differences in billing cycles - which denote the start date and end date of a billing period - across firms. In our sample, there are 16 unique billing cycles, where firm assignment to a billing cycle is based on geography. The staggering of billing cycles throughout a month provides a second source of cross-sectional variation in weather due to the fact that a hot day may be included in different billing "months" for firms on different bill cycles.

4. Empirical Specification

Using the dataset described in Section 3, we estimate the responsiveness of energy consumption to weather variation by contract type across consumption deciles in our sample. We seek to retrieve the dose response function of temperature on electricity use, and to measure how it differs across tenants as a result of exposure to different contract types.

Our basic empirical model is summarized by equation (1):

$$Y_{it} = \boldsymbol{\beta_d}[C_{zt} \times \mathbb{1}_{id}, H_{zt} \times \mathbb{1}_{id}] + \boldsymbol{\theta_d Tenant_i} \times [C_{zt} \times \mathbb{1}_{id}, H_{zt} \times \mathbb{1}_{id}]$$
$$+ \eta_i t + \alpha_t + \gamma_i + \varepsilon_{it} \quad (1)$$

where Y_{it} is the logarithm of monthly energy consumption for tenant i in billing month t, C_{zt} and H_{zt} are average daily cooling and heating degree days for a firm with billing month t in zip code z. A vector of indicator variables is denoted by $\mathbb{1}_{id}$ and set equal to 1 if tenant i has electricity demand in decile d (i.e. $d = \{1, ..., 10\}$), and zero otherwise. The indicator variable for whether a tenant i pays their own utility bills is interacted with each of the weather variables, $\mathbf{Tenant}_i \times [C_{zt} \times \mathbb{1}_{id}, H_{zt} \times \mathbb{1}_{id}]$.

Additional controls include $\eta_i t$, an account-specific time trend, γ_i, an account fixed effect, and α_t is a calendar month-by-year fixed effect. We can condition on this latter fixed effect since our identifying variation utilizes billing-month weather and consumption rather than calendar month variation. To adjust for serial correlation, standard errors are clustered at the building level.

Our empirical approach identifies the differential impact of weather shocks on energy usage across customers who pay and do not pay their own electricity bill, and is similar to the approach deployed in Jacobsen and Kotchen (2013). If the effect of tenants paying the utility bills (rather than owners) decreases energy use, we would expect to observe a negative coefficient on the interaction between Tenant$_i$ and C_{zdt} across each consumption decile. The effect of cooling degree days is the primary variable of interest because it is a strong predictor of air conditioning utilization, and therefore highly correlated with electricity consumption in the summer months.

5. Identification

Since contract type is not randomly assigned in our empirical setting, the main concern from the perspective of identification is that firms on a landlord-pay contract are selected in some unobservable way that relates to their latent dose-response function. An unbiased estimate relies on our main identifying assumption: conditional on observables and fixed effects, the dose response function differs only by contract type, and does not differ as a result of a reaction to the temperature gradient that correlates with unobservable firm attributes. Since this assumption is not directly testable, our strategy is to expose it to many opportunities to fail. This section describes the tests that we perform as well as the empirical evidence that allows us to proceed with confidence in a causal interpretation of our estimates.

5.1 Selection into Contract Type

We present three approaches to assess the possibility that tenants are able to select into a rental space with their desired contract type. Our first approach evaluates covariate balance among tenant-paid and owner-paid contracts in the full sample, which we implement both by examining summary statistics in the data and more formally by estimating logistic regressions of contract type on observables. Second, we exploit a policy change in Connecticut that relaxed restrictions on sub-metering retrofits after the end of our sample period. This enables us to (i) identify and (ii)investigate the characteristics and behavior of firms located in buildings that subsequently switched contract types. The third method is a deployment of Oster (2016) that places bounds on potential selection bias.

Balance on Observables: We begin by comparing owner and tenant-paid contracts, both in the full sample and for the top decile of users, across a number of observables that we hypothesize may be related to contract type. The last column of Table 2 presents the normalized difference in means between the two contract types in the full sample, where a normalized difference lower than 0.25 in absolute value is typically considered good overlap (Imbens and Wooldridge (2009)). As shown, the covariates are balanced along the rich set of covariates we observe. Since our main result will focus on the tenant-paid contract effect in the top consumption decile, Table 3 presents covariate balance for these users. While the consumption variables maintain good overlap in this sample, the number of stories has a normalized difference of -0.55 and the industry classifications for Finance, Education and Entertainment are slightly out of balance. Differences in building height and the lack of balance in the Finance category are driven by a small number of owner-paid buildings that are over nine stories and occupied by financial tenants. We later address these imbalances in a robustness test. Education and Entertainment each make up a small share of

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the sample, with 9 percent and 15 percent of firms in each industry, respectively. Notably, the most energy intensive industrial classifications display balanced shares of tenant-paid contracts.

Along the same lines, we estimate a logistic regression to examine the relationship between contract type and observable characteristics. Column (1) of Table 4 presents the results of a logistic regression of a tenant-paid utilities dummy, set equal to one if tenants pay their own utility bills, on firm-level observables in the full sample. Peak load and bill length are significant in predicting contract type. As shown in column (2), the effects of bill length and peak load on contract type are driven by outliers. After the omission of two firms with excessively high peak load and a few observations with abnormally long bill lengths, no observables are significant in predicting contract type. Column (3) restricts the sample to the top consumption decile and column (4) further restricts the sample by excluding buildings with more than nine stories. We find that with the exception of the number of stories, no observable is significant in predicting contract type, and that this effect is no longer present once we remove very tall buildings. The covariate overlap and logistic regression results suggest no fundamental relationships between the observables and contract type, and while this does not imply that unobservables are balanced across contract type, it provides a first line of evidence to support the plausibility of our main identifying assumption.

Finally, we examine the robustness of our results to concerns about sorting along a number of observables by augmenting equation (1) to incorporate other covariate interactions with CDD and HDD. This is reflected in equation (2),

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\begin{aligned}
Y_{it} = \boldsymbol{\beta_d}[C_{zt} \times \mathbb{1}_{id}, H_{zt} \times \mathbb{1}_{id}] + \boldsymbol{\theta_d Tenant_i} \times [C_{zt} \times \mathbb{1}_{id}, H_{zt} \times \mathbb{1}_{id}] \\
+ \boldsymbol{\psi X_i} \times [C_{zt}, H_{zt}] + \mathrm{B}_{it} + \eta_i t + \alpha_t + \gamma_i + \varepsilon_{it}, \quad (2)
\end{aligned}
$$

where $\boldsymbol{\psi}\boldsymbol{X_i} \times [C_{zt}, H_{zt}]$ is the covariate vector interacted with heating and cooling degree days, $\boldsymbol{X_i}$ includes indicator variables for building type and firm NAICS code, and B_{it} measures the number of days in the billing month (bill length) for firm i in billing month t.

Contract Switchers: Our second approach takes advantage of a policy change that occurred after the end of our sample period. Within our sample period, a ban on sub-metering retrofits in Connecticut made sorting by customers and building owners along contract type very costly, if not impossible. Customers that desired attributes of a building not sub-metered may have preferred to pay their own electricity and landlords may have preferred to offer tenant-paid utilities. However retrofitting buildings with unit-level electricity meters, a prerequisite for tenant-paid contracting, was not permitted. In 2013, about two years after our sample period ended, this restriction was lifted and landlords were allowed to retrofit buildings with sub-meters.

We use building-level tenancy contract information collected a year and a half after the Connecticut legislative change, in early 2015, to assess whether sorting based on energy consumption preferences might have occurred once sub-metering retrofits were allowed. Since the legislative change allowed a more flexible re-matching of tenants into contract type, this presents an opportunity to observe who switched, and to examine whether controlling for their identity changes our baseline results. Under the null hypothesis of "no selection", conditioning on the identity of these switchers should not alter our estimated treatment effect.

Roughly six percent of customers switched contract types, with 34 owners moving to a tenant-paid contract by early 2015 and 31 transitioning to an owner-paid

contract.[4] In Table 5 we show that total consumption, peak usage, and total bill is balanced across switchers and non-switchers.[5] The balance in energy consumption characteristics across these groups suggests that controlling for these users may not substantively change the results. Still, to test our null hypothesis directly, we build on our baseline specification and interact two "switcher" indicator variables - one for firms switching to tenant-paid contracts and a second for firms switching to owner paid contracts - with cooling and heating degree days.

Oster Bounds: Our final approach to testing our identifying assumption uses a new technique proposed by Oster (2016). This method requires the assumption that the relationship between treatment and unobservables can be recovered from the relationship between treatment and observables. If true, movements in the coefficient of interest and R-squared levels from the inclusion of control variables inform us about selection on unobservables. We retrieve the bounds in a post-estimation procedure and present these results in Section 6.

5.2   Time-Varying Unobservables

The assignment of bill cycles based on geography and our decision to exploit variation in weather across billing cycles raises the possibility that bill cycle might be correlated with the dose response function across contract type. We investigate this by testing if a systematic relationship between bill cycle and weather exists. A regression of weather on bill cycle finds that that the sixteen billing cycles are neither jointly nor individually significant in explaining cooling degree days or heating degree days.[6]

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[4]Given the long-term nature of building ownership and commercial sector contracts, it's unlikely that ownership of these buildings or the tenants occupying them changed over time. Mean lease length in the industries in our sample is over 4 years, with a 60% renewal rate (Fisher and Ciochetti (2007)).

[5]Interestingly, buildings that switch to a tenant-paid contract tend to be larger and taller, which suggests economies of scale to sub-metering.

[6]Results available from authors upon request.

Still, our empirical approach explicitly addresses this concern by conditioning on bill cycle in all our empirical specifications.

A related concern is that the dose response function to weather partly reflects differences in bill length (i.e. the number of a days in a billing month) across firm-months. This will confound our interpretation of the treatment effect if bill length is systematically related to contract type. We control for this possibility by including bill length as a control in equation (2), as noted above.

6. Results

Our findings suggest contract type induces economically and statistically significant impacts on consumption choices for the largest electricity consumers. The reduced form relationship between contract type, firm size, temperature and electricity consumption is presented in Figure 3. It plots electricity consumption against average temperature within 1-degree bins, across both contract types, for the bottom nine decile of firms in panel (a), and the top consumption decile in panel (b). Superimposed on each scatter plot is a lowess fit of consumption on temperature. This figure provides a preview to our formal regression results and points to three interesting patterns of firm behavior. First, as shown in panel (a), on average there is almost no discernible difference in consumption by contract type across the distribution of temperatures in the bottom nine consumption deciles. Second, in the top consumption decile, shown in panel (b), we observe a significant divergence in usage across contract types, with firms under owner-paid utility contracts exhibiting higher usage, relative to tenant-paid firms. Third, this difference in usage becomes more pronounced when air-conditioning demand rises. Consumption levels begin to diverge more sharply once temperature increases beyond approximately 65 F, the temperature at which demand for cooling typically begins (EPA (2014)).

Table 6 presents our formal regression results. Column (1) shows the effect of a regression comparing the differential impact of a weather shock on firms with a tenant-paid contract type relative to an owner-paid contract, controlling for firm, month-year fixed effects and firm-specific time trends. We find that without conditioning on consumption decile there is no difference in the effect of weather shocks on consumption among tenant-paid versus owner-paid contracts. In the remainder of Table 6, we report results from the estimation of equations (1) and (2). Column (2) reports results from our base specification as shown in equation (1), where we introduce tenant-paid contract interactions with CDD and HDD across all ten consumption deciles; column (3) controls for the differential effect of temperature shocks on switchers and column (4) further conditions on the interaction of CDD and HDD with building and industry type, as shown in (2). Column (5) presents a robustness check which excludes outliers from the sample, leaving us with a sample in which all observables for firms in the top consumption decile are balanced across contract type.[7]

Our results indicate that a split incentive problem leads to overconsumption of energy among the top decile of electricity consumers. This effect is quantitatively and qualitatively robust to several specifications, suggesting that firms on a utilities included contract exhibit a different dose response function to weather than firms who pay their own utility bills.[8] Focusing on our preferred specification in column (4), we find that a tenant-paid contract leads to about a 1.4 percent decrease in kWh per average daily CDD for the top decile of electricity consumers. Over the course of the year, which has an average daily CDD of 2.1, this translates into a 2.9

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[7]We exclude two firms with high peak load, four buildings with ten or more stories and bill length outliers in the sixth decile.

[8]Note that the switchers interaction coefficients are not reported for space considerations, but they are insignificant in all specifications in which they appear.

percent decrease in annual electricity usage among the top decile of users. Framed differently, for firms on a tenant-paid contract a one standard deviation increase in daily CDD leads to a 5 percent reduction in monthly usage relative to utilities included firms. In contrast, contract type does not statistically impact consumption decisions for the other 90 percent of commercial firms. This large divergence in response to contract type based on firm size points to a first source of heterogeneity in response to treatment, and potentially large savings from the targeted deployment of a policy instrument.

A second source of heterogeneity results from seasonal variation in the treatment effect. We find that the split incentive can lead to significant increases in electricity usage but only during the hot summer months. This can be seen in Figure 4, which illustrates the estimated difference in usage across contract type for each month in our sample. It is obtained by multiplying the treatment effect reported in column (4) of Table 6 by average daily CDDs in a given month. In August, switching from an owner to a tenant-paid contract would reduce electricity consumption by about 13%. The summer response is consistent with a framework in which demand for electric AC during these hot months drives the divergence in the dose response function across owner and tenant-paid contracts. [9]

Though contract type only influences electricity choices for a narrow set of customers during a concentrated period of time, restructuring contract type has meaningful implications for aggregate electricity usage. This is because the responsive firms are the largest electricity consumers and are quite sensitive to hot temperatures. A policy that switched the largest decile of electricity consuming firms from an owner to tenant-paid contract would result in annual electricity savings per firm

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[9]The coefficients on heating degree days (not reported) are not statistically significant in any specification. Since most firms in Connecticut use natural gas or fuel oil for heating, it is not surprising that the dose response function for heating does not vary across contract type.

of roughly 19,200 kWh. Comparing these savings to the total quantity of electricity consumed by all commercial firms in our sample, we find that this policy change would lead to a 1.4 percent reduction in total electricity usage.

We also estimate the effect of contract type on electricity expenditure by estimating (2), the fully controlled specification, with log monthly bill as the dependent variable; results are shown in Table 6 column (6). The estimated treatment effect in the top decile is a 1.2 percent decrease in monthly bill per CDD. The value of total bill savings among these high consumers is approximately \$315 per summer month. In the month of August the savings represent a 10% reduction in electricity expenditures.

To further gauge the robustness of our results to potential selection on unobservables, we apply the bounds analysis proposed by Oster (2016). We make an equal selection assumption which implies that any residual omitted variable bias is a function of (i) the treatment coefficient after the inclusion of covariates and (ii) R-squared values before and after the inclusion of covariates. Given our rich set of controls, the equal selection assumption is likely conservative, as it assumes that any remaining unobservables are at least as important as the observables in explaining the treatment (Oster (2016) and Altonji et al. (2008)). Table 7 reports the identified set estimates from two different specifications with log usage and log bill as the dependent variables, respectively, in the full sample. They assume that the maximum possible R^2 is 0.98, given the estimated 2 percent measurement error in electricity meter readings (Dong et al. (2005), Reddy et al. (1997)). As shown in Table 7 we continue to detect a split incentives effect after accounting for any remaining selection on unobservables. A tenant-paid contract induces at minimum a monthly electricity

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and bill saving of 0.7 and 0.6 percent per CDD, respectively.[10]

6.1 Social benefits and payback period

In this section we estimate the avoided emissions, decline in environmental damages and payback period from shifting to a tenant-paid utility contracts in our sample. We begin by identifying the per kWh emissions rates and marginal damages of four pollutants regulated by the federal government: NO_X, SO_2, $PM_{2.5}$ and CO_2. We choose these four because of their links to human health damages and contributions to climate change. For NO_X, SO_2 and CO_2, the Environmental Protection Agency's eGRID database provides 2009 emission rates for the New England subregion, measured as tons emitted per MWh of electricity produced.[11] The $PM_{2.5}$ emission rate estimate is obtained from Connors et al. (2005). Marginal damage estimates for NO_X, SO_2 and $PM_{2.5}$ come from Muller and Mendelsohn (2007), and marginal CO_2 damages represent an average of the estimates presented in IWGSCC (2015) and IWGSCC (2010).[12]

We then combine the above marginal damages and emissions rates with our estimated treatment effects to bound the social benefits of switching from an owner to tenant-paid contract. For the top decile of electricity consumers, we use the per CDD coefficient from column (4) of Table 6, our preferred specification, as an upper bound estimate (this is also the Oster upper bound), and the Oster lower bound savings estimate reported in Table 7. We multiply these by the average CDD in the summer months for each firm with a tenant-paid utility contract to arrive at a per

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[10]All the energy and bill savings ranges reported in the paper are based on these Oster identified set estimates.

[11]The eGRID database is available at the EPA's website at www.epa.gov/energy/egrid.

[12]IWGSCC (2015) presents an updated social cost of carbon estimate relative to IWGSCC (2010), and is a better reflection of the scientific consensus on climate change impacts. However the 2010 report coincides with our sample period which is why we also choose to include it.

firm annual electricity savings of 9,700 to 19,200 kWh. These consumption savings are used to form our bounds for avoided damages from the four pollutants.

The upper and lower bound estimates for avoided pollution-related external costs are presented in Table 8. Annually, the per firm value of avoided damages ranges from \$111 to \$221. If we add to this the private bill savings of \$677 to \$1265 per firm-year, the annual firm-level social benefit of switching from an owner to tenant-paid contract amounts to \$788 to \$1709. For comparison, these savings are about fifteen times larger than the household-level savings attributable to building energy standards and over fifty times larger than the household bill savings from tenant-paid heating in apartment buildings in the northeastern US (Jacobsen and Kotchen (2013), Levinson and Niemann (2004)).

At the national level, restructuring rental contracts for the largest ten percent of commercial firms would produce energy savings exceeding those from restructuring rental contracts for all residential users who don't pay for their utilities.[13] It would also save between 615-1200 thousand tons of CO_2 per year or between 3.3 to 6.6 times the average annual savings achieved from Weatherization Assistance Program retrofits performed in a given year.[14]

Finally, we use data on the costs of sub-metering to calculate back-of-the envelope estimates of the payback period from sub-metering individual units and shifting to a tenant-paid contract. Sub-meter costs range from \$250-\$1000 per unit (Pike

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[13]There are 131 million residential electricity customers in the US, of which 10.4 million are rented with utilities included (EIA (2009)). Assuming they save 0.7% per household (Levinson and Niemann (2004)), total savings are 141 million kWh per year. There are approximately 17.6 million commercial sector electric customers in the US (EIA (2017)), 50 percent of which rent space, or about 8.8 million customers. Suppose 20 percent (1.76 million) have an owner-paid utilities contract, the same share as in Connecticut. The top consumption decile, 176,000 customers, save a total of 181 million kWh per year (1.3%) from a switch to tenant-pay contracts.

[14]An average of 175,000 WAP retrofits are performed every year, which save approximately 1.06 tons of CO_2 per household per year (Fowlie et al. (2015), DOE (2017), EIA (2010)). These retrofits therefore save 186,000 tons of CO_2 every year.

Research (2012), White (2012), Millstein (2008)). Given our average estimated annual bill savings of \$970 (the average of the bill savings obtained using the Oster identified set estimates), and assuming a unit-level sub-meter cost of \$625, the payback period is less than one year, well below the payback threshold for most firms' energy conservation investments (Anderson and Newell (2004)).[15] These values also compare quite favourably to other cost-effective energy efficiency programs (Allcott and Mullainathan (2010)). With a unit- or firm-level sub-meter cost of \$625 incurred up-front and an average annual treatment effect of 14,500 kWh saved among high consuming firms, the cost effectiveness is 4.3 cents per kWh after the first year, 2.1 cents per kWh after two years, and 1.4 cents after 3 years, assuming the annual electricity savings persist at the same level.

6.2 The Non-Response of Most Commercial Firms

While we estimate that contract type has a sizable effect on electricity usage for the largest firms, one unanswered question is why the remaining 90% of commercial firms do not respond to contract type. In our view, the most likely explanation is that even when tenants face the costs of their energy consumption choices, the net benefits of decreasing electricity consumption or investing in energy efficiency are negative. This is consistent with a growing strand of research that documents negative realized net benefits from energy efficiency investments (Hassett and Metcalf (1999), Fowlie et al. (2015)). It is also consistent with (potentially rational) inattention that leads commercial firms to be unresponsive to some financial incentives (Jessoe and Rapson (2015)). In this section we provide evidence for this hypothesis by performing a coarse

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[15]In most states sub-meter system costs can be recovered through surcharges on tenant utility bills. This enables owners to recover their investments costs. If the owner's surcharge doesn't recover the full value of the savings, the payback period may be longer, but our estimates would still represent a social payback period.

cost-benefit analysis for a common behavioral change firms can undertake to save energy. We then go on to document other potential explanations for why firms may not mitigate their energy consumption under a tenant-paid contract.

Let us consider the electricity choices of an office building, the sector that makes up the largest share of buildings in our sample. Building overcooling and overheating are common in office buildings, and some occupants' behavioral responses, such as keeping personal heaters or fans on, also contribute to increasing energy consumption. Derrible and Reeder (2015) suggest that overcooling increases electricity consumption by 8 percent per year, and Sanchez et al. (2007) estimate portable heaters consume 329 kWh per year. Using these numbers, for the bottom nine deciles of our sample, the combination of overcooling and space heating amounts to 4300 kWh of annual electricity consumption, or $530 on an annual basis. Since addressing overcooling would likely require hiring a property manager or engineer to monitor and adjust air conditioner and chiller operation, and may compromise comfort among some occupants, the total cost of avoiding overcooling may well exceed the $530 reduction in expenditure.

Other explanations could also account for the lack of a treatment effect across most firms. One possibility is rational inattention. Comparing the $677 to $1265 annual bill saving from a tenant-paid contract to the average commercial unit size in Connecticut, 14,000 square feet, suggests an average annual bill saving of about 4.8-9 cents per square foot. This represents about 0.2 percent of the average annual revenues per square foot in office and retail industries, and highlights that the savings smaller firms forego likely represent a very small share of their annual sales. After accounting for the time and effort required to accurately assess the energy savings from different energy efficiency investments, firms may be rationally inattentive to potential energy savings since the savings are comparatively quite small (Sallee

(2014)).

7. Conclusion

We measure the 'split incentive' effect of tenancy contract type using a unique empirical setting and novel dataset of tenancy contracts and energy use among commercial sector clients. Our approach takes multiple steps to probe and address the empirical challenge of separately identifying the split incentive problem from sorting. We show that contract type is not systematically correlated with a rich set of observable characteristics; that changes in contract choice at the building level are not correlated with energy consumption; and that our result is robust to a conservative assumption about any remaining correlation between unobservable characteristics and our treatment.

Our results indicate heterogeneous returns to a tenant-paid contract, with a positive and significant effect of contract type only in the top decile of electricity consuming firms. The results are consistent with privately optimal decision-making by firms since the bill savings from conservation behavior are relatively small across most of the consumption distribution, likely not large enough to justify energy efficiency investments or behavioral changes.

This study is a rare contribution to the split incentive literature on commercial customers that credibly addresses sorting. The result implies a strong case for encouraging tenant-paid energy contracting among large commercial and industrial customers. For the largest decile of electricity consumers, we find that firms who pay their own utility bills consume about 3% less electricity annually than tenants whose utility bills are bundled into rents and save between \$677 and \$1265 on their annual electricity bills. These reductions lead to a 1.4 percent saving in total electricity consumed by all firms in our sample, and generate annual external benefits of \$111 and

$221. The payback period from sub-metering and switching to a tenant-paid contract is less than one year, and the cost-effectiveness among high consumers is comparable to behavioural and other interventions that have recently received significant attention in the energy setting (Allcott (2011), Allcott and Mullainathan (2010)). A targeted policy of sub-metering and tenant-paid contract promotion would likely be a net beneficial addition to the portfolio of mitigation strategies utilized by policy-makers.

When compared to other locations, our estimated consumption and bill savings may present a lower bound. We study the question of split-incentives in Connecticut, a location where most consumers rely on natural gas for heating and where summer temperatures may be relatively mild. In locations with a high penetration of electric heating, we may find that contract type impacts demand for heating. In the southwestern and southeastern states with warmer temperatures and higher air conditioning usage, the savings from restructuring contract may also be larger.

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Figure 1: UI Territory
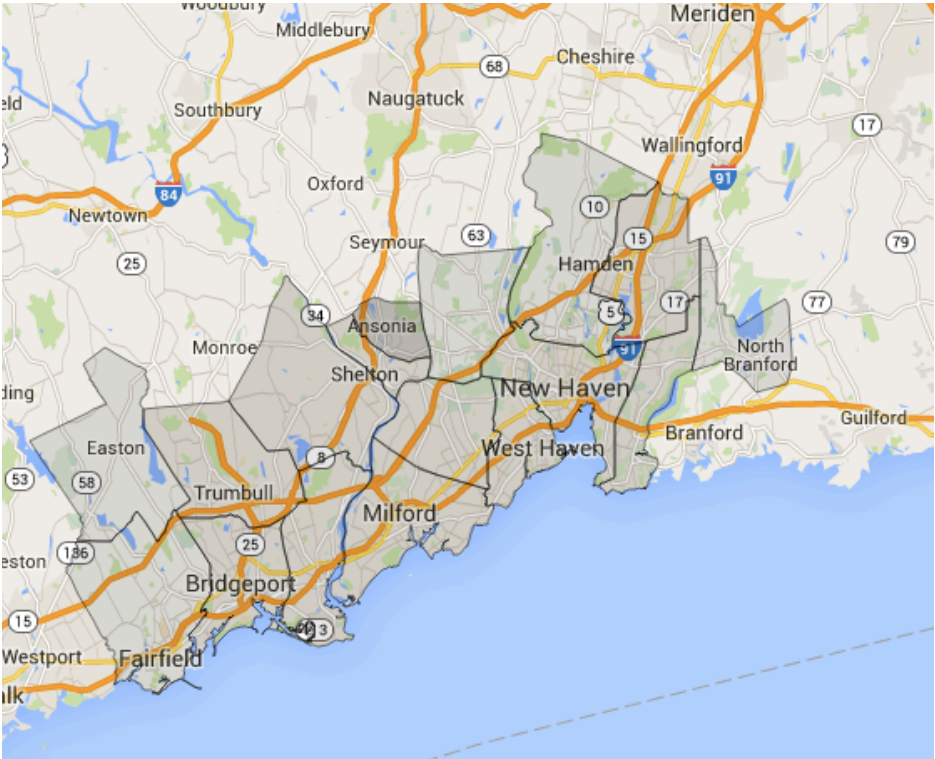
Notes: United Illuminating's service territory. It offers electricity distribution services to 17 counties in Connecticut, an area totaling 335 square miles.

Figure 2: Weather Data Variation
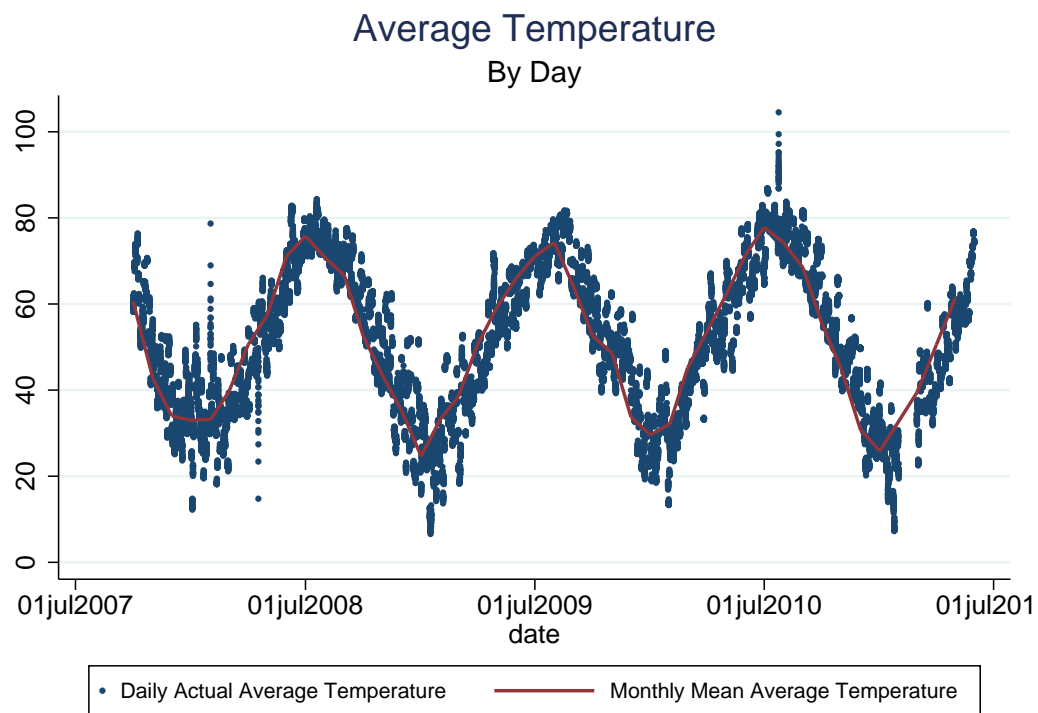
Notes: Average daily temperature in UI's service territory between October 2007 and May 2011, at the zip code level. Despite the relatively small region, there is visible cross-sectional variation in daily temperatures, with summer temperatures varying between 5 to 10 degrees across zip codes. Temperature variation within a zip code is also possible, due to differences in billing cycles across firms

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Figure 3: Consumption By Contract Type

(a) Bottom Nine Deciles
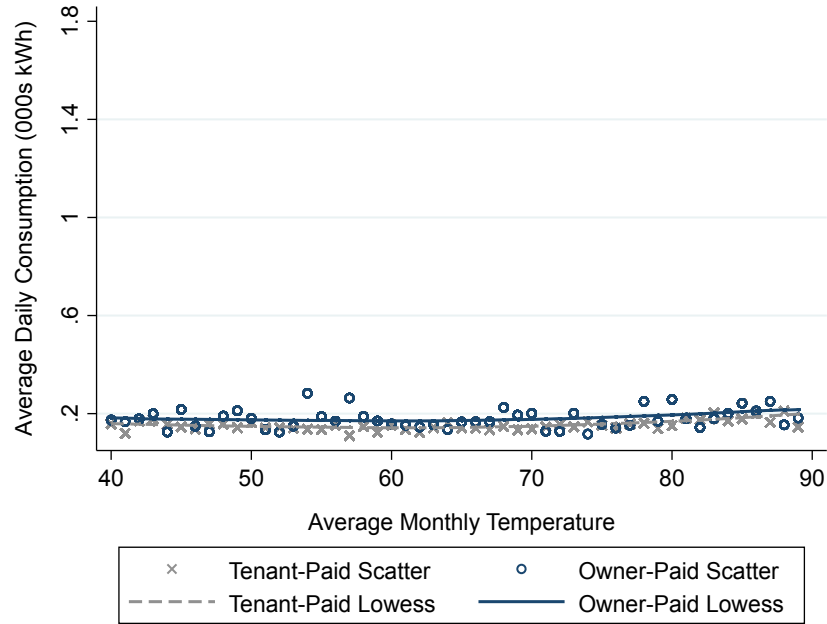
(b) Highest Consumption Decile
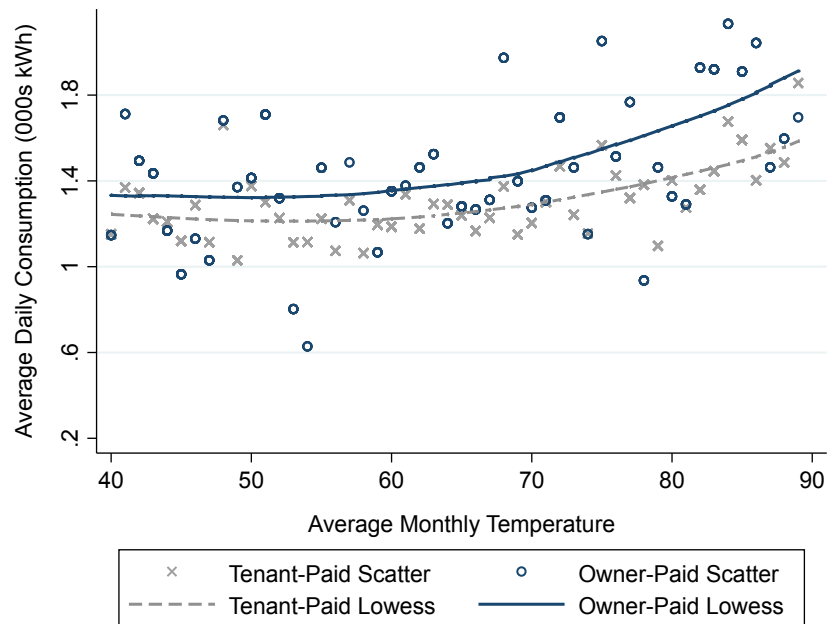
Notes: Each scatter plot presents monthly electricity consumption against average temperature within 1-degree bins, for the bottom nine decile of firms in panel (a), and the top consumption decile in panel (b). The observations are color-coded by contract type, in both the bottom nine deciles (panel (a)), and the top consumption decile (panel (b)). The solid lines are a lowess fit of the same data.

Figure 4: Average Consumption Reduction Implied by Treatment Effect (Montly, Top Consumption Decile)
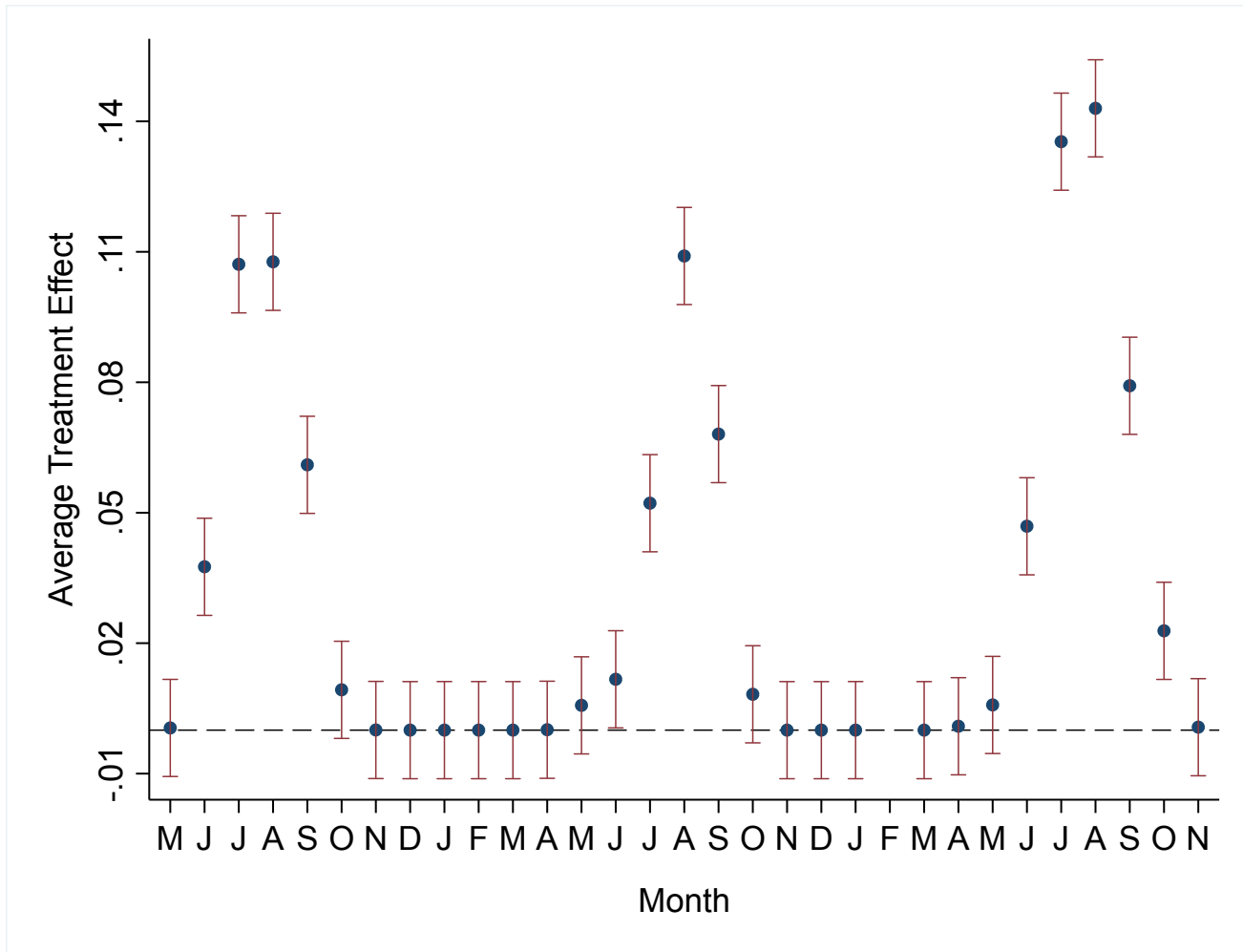
Notes: The Figure shows average treatment effect on consumption in the top consumption decile, shown as blue circles. It is obtained by multiplying the estimated treatment coefficient by monthly cooling degree days, in a regression that corresponds to column (4) in Table 6. The resulting firm-level monthly treatment effects are then averaged over each month in the sample. The red hatched lines represent 95 percent confidence intervals for the average consumption effect, obtained by adding and subtracting s.e. × 1.96 from the top decile consumption effect, where s.e. is the standard error of the top decile estimate in specification (5).

Table 1: Property Types

	Property Type	Customers	Obs.
1	Office	805	29,846
2	Industrial	252	8,876
3	Retail + Flex	69	2,240

Notes: Property type identifies the primary use of the buildings in our sample. The predominant share is made up of office buildings (72 percent), followed by industrial buildings (22 percent), and finally by retail and flex buildings, where flex buildings combine office and retail functions (6 percent).

Table 2: Summary statistics and covariate balance in full sample

	All Firms				
	Tenant Pays		Owner Pays		Norm. Diff.
	Mean	St. Dev.	Mean	St. Dev.	
kW	27.3	42.9	33.5	61.4	-0.08
kWh (000s)	7.7	13.8	9.0	17.1	-0.06
Bill ($)	627	999	720	1220	-0.06
Bill Length	30.3	1.3	30.4	1.3	-0.05
Building S.F. (000s)	57.2	59.7	66.8	93.6	-0.09
Year Built	1974	26	1968	33	0.14
Building Stories	2.6	1.6	3.4	3.1	-0.23
Industry	0.12	0.33	0.10	0.31	0.04
Trade, Accommodation	0.15	0.36	0.12	0.33	0.06
Finance, Real Estate, Management	0.47	0.36	0.55	0.50	-0.13
Education, Health, Pub. Admin.	0.19	0.36	0.18	0.38	0.02
Entertainment, Recreation, Services	0.07	0.36	0.05	0.21	0.05
Northeast	0.27	0.44	0.31	0.45	-0.06
Southeast	0.20	0.40	0.22	0.42	-0.03
Northwest	0.13	0.34	0.06	0.23	0.17
Southwest	0.40	0.49	0.41	0.49	-0.01
Observations	34,304		6,658		
Firms	948		178		

The normalized difference measures the degree of overlap for each covariate across the treated
and control samples. A normalized difference lower than 0.25 is typically considered good overlap.

Notes: The normalized difference measures the degree of overlap for each covariate across the treated and control samples. A normalized difference lower than about 0.25 is typically considered good overlap.

Table 3: Summary statistics and covariate balance in top consumption decile

| | Top Decile Firms | | | | |
| | Tenant Pays | | Owner Pays | | Norm. Diff. |
	Mean	St. Dev.	Mean	St. Dev.	
kW	132.4	71.2	164.2	120.9	-0.23
kWh (000s)	40.6	24.1	44.5	34.1	-0.09
Bill ($)	3002	1759	3276	2403	-0.09
Bill Length	30.4	1.3	30.4	1.3	-0.01
Building S.F. (000s)	86.8	79.7	144.9	146.4	-0.35
Year Built	1978	19	1973	24	0.16
Building Stories	3.0	2.4	6.1	5.1	-0.55
Industry	0.22	0.41	0.18	0.39	0.07
Trade, Accommodation	0.09	0.28	0.04	0.20	0.15
Finance, Real Estate, Management	0.46	0.50	0.77	0.42	-0.47
Education, Health, Pub. Admin.	0.09	0.29	0.00	0.00	0.31
Entertainment, Recreation, Services	0.15	0.35	0.00	0.00	0.43
Northeast	0.28	0.45	0.27	0.44	0.02
Southeast	0.18	0.38	0.32	0.47	-0.23
Northwest	0.12	0.32	0.00	0.00	0.38
Southwest	0.43	0.50	0.41	0.49	0.03
Observations	3,202		703		
Firms	91		19		

Notes: The normalized difference measures the degree of overlap for each covariate across the treated and control samples. A normalized difference lower than about 0.25 is typically considered good overlap.

Table 4: Logistic Regression

| | Dependent Variable: Tenant Pays | | | |
| | Full Sample | | Top Decile | |
	(1)	(2)	(3)	(4)
kW	-0.006*	-0.004	-0.006	-0.006
	(0.004)	(0.004)	(0.004)	(0.006)
kWh	0.019	0.022	0.022	0.008
(Thousands)	(0.021)	(0.023)	(0.019)	(0.020)
Bill	-0.057	-0.229	-0.162	-0.049
(Thousands)	(0.299)	(0.311)	(0.247)	(0.313)
Bill Length	-0.023**	-0.012	0.020	0.027
	(0.009)	(0.011)	(0.022)	(0.025)
Stories	-0.247	-0.247	-0.383***	-0.349
	(0.152)	(0.152)	(0.147)	(0.247)
Building Size	0.004	0.004	0.019	0.019
(Thousands)	(0.004)	(0.005)	(0.017)	(0.017)
Year Built	0.007	0.007	0.000	0.017
	(0.006)	(0.006)	(0.015)	(0.013)
Property Type	0.048	0.072	0.246	0.339
	(0.532)	(0.526)	(0.510)	(0.415)
Region	0.008	0.021	-0.257	-0.224
	(0.165)	(0.165)	(0.289)	(0.299)
Industry	0.037	0.028	0.488	0.359
	(0.159)	(0.159)	(0.377)	(0.334)
Mand. TOU	0.959	1.180	0.684	1.362
	(0.987)	(1.140)	(1.809)	(2.206)
Vol. TOU	-0.152	-0.155	-0.011	0.389
	(0.270)	(0.271)	(1.425)	(1.467)
Observations	40,962	39,829	3,905	3,664
Accounts	1,126	1,124	110	103
Pseudo R squared	0.04	0.04	0.19	0.17

Notes: Results of a logistic regression of a tenant-paid dummy on the observable variables. Column (1) shows the full sample results; column (2) shows the full sample without two high-consuming accounts and large bill length observations in the sixth decile; column (3) shows same logistic specification results in the top decile; and column (4) shows the top decile results without out-of-balance stories observations (buildings greater than 9 stories). Robust standard errors clustered at the building level in parentheses, ***p<0.01, ** p<0.05, * p<0.1.

Table 5: Covariate balance in switchers to tenant-paid utilities contract

	No Switch	Switch to Tenant-Paid	Norm. Diff.	Switch to Owner-Paid	Norm. Diff.
	Mean (S.D.)	Mean (S.D.)		Mean (S.D.)	
kW	27.7 (44.5)	31.4 (67.3)	0.05	41 (65.7)	0.17
kWh (000s)	7.8 (13.9)	9.8 (22)	0.08	10.7 (16.4)	0.13
Bill ($)	632 (1004)	748 (1520)	0.06	861 (1190)	0.15
Building S.F. (000s)	61.3 (73.5)	197.8 (113.6)	1.01	44.6 (36.8)	-0.20
Year Built	1973 (27.3)	1986 (9.5)	0.45	1974 (14.3)	0.03
Building Stories	2.84 (2.55)	13.01 (7.86)	1.23	2.38 (0.97)	-0.17
Industry	0.12 (0.32)	0.04 (0.18)	-0.22	0.06 (0.24)	-0.15
Trade, Accommodation	0.15 (0.35)	0 (0)	-0.43	0.32 (0.47)	0.29
Finance, Real Estate, Management	0.48 (0.5)	0.89 (0.32)	0.69	0.5 (0.5)	0.03
Education, Health, Pub. Admin.	0.19 (0.39)	0.03 (0.17)	-0.38	0.09 (0.29)	-0.21
Entertainment, Recreation, Services	0.07 (0.25)	0.05 (0.22)	-0.06	0.02 (0.15)	-0.15
Northeast	0.26 (0.44)	0.09 (0.28)	-0.32	0.79 (0.41)	0.88
Southeast	0.21 (0.41)	0.77 (0.42)	0.95	0.1 (0.29)	-0.22
Northwest	0.12 (0.32)	0.13 (0.33)	0.02	0.04 (0.19)	-0.21
Southwest	0.42 (0.49)	0.02 (0.14)	-0.8	0.08 (0.26)	-0.61
City	0.31 (0.46)	0.8 (0.4)	1.03	0.13 (0.34)	-0.42
Observations	39,544	1,271		1,145	
Firms	1,086	34		31	

Notes: The normalized difference measures the degree of overlap for each covariate across the treated and control samples. A normalized difference lower than about 0.25 is typically considered good overlap.

Table 6: Split Incentive Effect By Consumption Decile

Dependent variable:	Log Usage					Log Bill
	(1)	(2)	(3)	(4)	(5)	(6)
Tenant x CDD	0.0001					
	(0.0001)					
Tenant x CDD (10th Dec.)		-0.013**	-0.013**	-0.014**	-0.013**	-0.012***
		(0.006)	(0.006)	(0.006)	(0.005)	(0.004)
Tenant x CDD (9th Dec.)		0.001	0.001	0.005	-0.006	-0.007
		(0.009)	(0.010)	(0.010)	(0.008)	(0.007)
Tenant x CDD (8th Dec.)		-0.001	-0.001	0.005	0.001	-0.001
		(0.007)	(0.007)	(0.007)	(0.008)	(0.005)
Tenant x CDD (7th Dec.)		-0.004	-0.004	-0.001	-0.002	-0.002
		(0.007)	(0.007)	(0.008)	(0.008)	(0.006)
Tenant x CDD (6th Dec.)		0.010	0.010	0.014*	0.010	0.008
		(0.008)	(0.008)	(0.007)	(0.009)	(0.006)
Tenant x CDD (5th Dec.)		0.003	0.003	0.005	0.004	0.003
		(0.007)	(0.007)	(0.008)	(0.008)	(0.005)
Tenant x CDD (4th Dec.)		0.009	0.009	0.012	0.010	0.008
		(0.011)	(0.011)	(0.011)	(0.012)	(0.007)
Tenant x CDD (3rd Dec.)		-0.017	-0.017	-0.017	-0.021	-0.012
		(0.014)	(0.014)	(0.014)	(0.015)	(0.009)
Tenant x CDD (2nd Dec.)		0.005	0.005	0.005	0.002	0.004
		(0.010)	(0.010)	(0.010)	(0.010)	(0.005)
Tenant x CDD (1st Dec.)		-0.010	-0.011	-0.009	-0.017	-0.007
		(0.012)	(0.012)	(0.013)	(0.012)	(0.007)
Account & Time F.E.s, Acct. Trend	YES	YES	YES	YES	YES	YES
Switchers Controls	YES	NO	YES	YES	YES	YES
Other Covariate Interactions	YES	NO	NO	YES	YES	YES
Covariate Balance Robustness	NO	NO	NO	NO	YES	YES
Observations	40,962	40,962	40,962	40,962	39,153	39,153
Accounts	1,126	1,126	1,126	1,126	1,104	1,104
R-squared (within)	0.08	0.08	0.08	0.09	0.09	0.26

Notes: Column (1) presents results without decile interactions. Columns (2)-(4) presents results in the full sample. Column (5) presents a robustness check with balanced building stories, bill length, and peak consumption. Column (6) presents the same specification as column (5) but with the logarithm of monthly bill as dependent variable. Robust standard errors clustered at the building level in parentheses, ***$p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 7: Oster Bounds for Monthly Usage and Bill

Log Usage		
	Coefficient	R-Squared
Uncontrolled	-0.021	0.60
Controlled	-0.014	0.90
Identified Set Estimate		
Lower Bound	-0.014	
Upper Bound	-0.007	

Log Bill		
	Coefficient	R-Squared
Uncontrolled	-0.021	0.70
Controlled	-0.012	0.94
Identified Set Estimate		
Lower Bound	-0.012	
Upper Bound	-0.006	

Notes: The Oster bounds present an identified set of treatment effect coefficients by accounting for residual omitted variable bias through an equal selection assumption. The omitted variable bias is assumed to be a function of the treatment coefficient and R-squared values before after the inclusion of covariates, as well as the maximum theoretically possible R-squared, namely from a regression on consumption and all possible observable and unobservable controls. This maximum R-squared may not be 1 if there is measurement error in the dependent variable.

Table 8: External and Private Benefits Per Firm

	External		External + Private Benefits	
	Low $	High $	Low $	High $
SO$_2$	8.21	16.33	685	1503
NO$_x$	0.75	1.50	678	1489
PM$_{2.5}$	0.38	0.76	677	1488
CO$_2$	101.95	202.91	779	1690
Total	111.29	221.50	788	1709

Notes: External benefits measure the annual per-firm reduction in pollution damages from lower electricity consumption. External plus private benefits measure the sum of external and private benefits, where private benefits are the annual bill savings noted in the text ($677-$1487). The low and high values are from the Oster identified set estimates of electricity saved, discussed in the text.