DEEP

Davis Economics Energy Program

DEEP WP 015

Utilities Included: Split Incentives in Commercial Electricity Contracts

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January 2018

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January 22, 2018

Abstract

The largest decile of commercial electricity customers comprises half of commercial sector electricity usage. We quantify a considerable split incentives problem that exists when these large firms are on electricity-included property lease contracts. Controlling for a rich set of variables that may correlate with selection into contract type, we use exogenous variation in weather shocks to show that customers on tenant-paid contracts use up to 14 percent less electricity in summer months. The policy implications are promising. Nationwide energy savings from aligning incentives for the largest decile of commercial customers would substantially exceed savings from fixing the split incentives problem 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, and public benefits are significant.

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

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1. Introduction

In the U.S., roughly 17 percent of commercial building occupants rent space with electricity bundled into their monthly rent. The structure of these rental contracts implies that these commercial tenants face zero marginal cost of consuming electricity. This misalignment between tenant and landlord incentives leads to overconsumption of energy and overproduction of pollution that Pigouvian taxes are not well suited to correct (Jaffe and Stavins (1994), Gillingham and Palmer (2014)). The welfare costs from excess energy use may be large since the commercial sector accounts for over 35 percent of end-use electricity consumption in the U.S. Addressing this misalignment has been acknowledged by energy economists, regulators and industry alike as a promising area for energy savings and cost-effective pollution abatement (IBE (2011), ASHRAE (2012), USGBC (2013)). Nevertheless, little evidence exists about the magnitude of this "split incentives" problem in the commercial sector.

In this paper, we estimate the reduction in electricity use from switching commercial customers on electricity-inclusive rent contracts to tenant-paid utility contracts, a distinction we refer to throughout as "contract type". Our results suggest 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 utility contract would reduce electricity usage by roughly 3 percent over the course of a year and 14 percent in the summer months. These annual savings among high consumers are comparable to popular energy conservation measures such as home energy reports, which produce average savings of approximately 2 percent (Allcott (2011)). Furthermore, the savings occur at times when the value of electricity is likely to be high: during the hottest days of the year. Contract type, however, does not measurably impact consumption decisions for the smallest 90 percent of commercial customers. This heterogeneous response is consistent with a setting in which the bill savings from changing consumption do not cover the adjustment costs for small firms.

Our empirical approach compares changes in electricity use in response to changes in temperature across firms in each contract type. We use the staggering of electricity billing periods across firms to generate exogenous cross-sectional variation in local weather exposure within a calendar billing month. We combine these data with monthly bills from 1,126 commercial firms serviced by United Illuminating, 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. The resulting panel dataset allows us to examine the differential impact of local weather shocks on electricity use across contract types, controlling for a wide range of potential confounders.

Our identification strategy addresses potential selection into contract type based on firm or building attributes. In our sample, firms on owner- and tenant-paid contracts differ on some building attributes, raising concerns about what can be learned from a simple levels comparison of electricity use across contract types. Instead, we compare the temperature response *gradient* across contract type. This permits us to achieve identification under weaker assumptions, as we can rule out some channels of selection into contract type based on fixed firm or building unobservables.

Under our strategy, identification may be compromised if selection into contract type occurs based on unobservable characteristics that are correlated with the temperature response gradient. We present three pieces of empirical evidence that support our identifying assumption. First, motivated by recent work demonstrating that the electricity response to temperature shocks meaningfully differs across certain building attributes, we control for the possibility that the response gradient is heterogeneous in observable building attributes (Novan et al. (2017)). After controlling for interactions between temperature and attributes such as building age and industry type, our results are unchanged. Second, we use a change to a Connecticut metering regulation, legislated after the end of our sample period, that altered building owners' ability to select into contract type. This provides us an opportunity to explicitly control for the temperature response gradient of firms located in buildings that switched contract types shortly after the change, and also test whether they exhibit a differential response gradient (they do not). Third, we assess the effect of potential correlations between any remaining unobservable characteristics and the treatment, as described in Oster (2016). This places bounds on the potential bias from selection on unobservables. Each of these tests exposes our identifying assumption to an opportunity to fail, and the results of each test support our main conclusions.

Given the size of the responsive firms, the estimated treatment effect translates into significant benefits from aligning these split incentives. If incentives were aligned among the largest decile of commercial customers nationwide, total energy savings would be roughly three times the savings produced by solving the split incentives problem for the entire U.S. residential electricity sector.[1] The magnitude of our results and the relative size of large commercial firms are the primary factors leading to this potentially surprising result. Though the number of commercial customers affected by the split incentives problem is small relative to residences, these customers use much more energy. Thus, addressing the commercial split incentive problem requires a fraction of the contact points (e.g. sub-meter installations) relative to the residential sector, while likely leading to greater energy savings. Our estimates imply greenhouse gas reductions of between 615-1200 thousand tons of CO_2 per year, or (to give a sense of scale) roughly 3.3 to 6.6 times the average annual savings from yearly Weatherization Assistance Program retrofits. These savings are achievable 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.

This work makes four main contributions to the academic literature and environmental policy discussion. First, compared to the residential setting where a growing literature points to the potential and limitations of energy efficiency and contracting solutions (Gillingham et al. (2012), Hassett and Metcalf (1999), Fowlie et al. (2015), Elinder et al. (2017)), little is known about how contracting influences commercial users. We provide a commercial counterpart to existing residential estimates on the split incentives problem. Second, our identification strategy makes several advances towards credibly estimating the magnitude of the split incentives problem. The response gradient, temperature-characteristic interactions, contract switcher controls, and Oster bounds each provide support for the identifying assumption and extend the existing literature on split incentives. Third, our results reveal substantial heterogeneity in firm responsiveness to contract type and point to the importance of looking beyond average treatment effects. Lastly, our results suggest a targeted prescriptive policy of tenant-paid contracts would be a net beneficial

[1] We describe the basis for this claim in Section 5.2. Under what we consider to be an extremely conservative combination of assumptions, the savings ratio is still greater than one.

greenhouse gas abatement strategy.

The rest of the paper is organized as follows. Section 2 reviews the academic literature and discusses our empirical setting. Section 3 describes the data. Section 4 discusses identification and presents our empirical specifications. Section 5 presents our empirical results and explores policy implications. Section 6 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 or underinvestment in energy effiency (Murtishaw and Sathaye (2006), Blumstein et al. (1980)). One frequently studied split incentive principal agent problem takes the form of a tenant-paid contract and underinvestment in energy efficiency by the landlord. If tenants are not able to perfectly observe efficiency levels and thus are unwilling to pay a rent premium for energy efficiency, owners may forgo energy conservation investments (Davis (2012), Myers (2014)). In contrast, our focus is on the split incentive problem arising 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. Given that about 50 percent of office and retail buildings are tenanted, or non-owner-occupied, the commercial sector has the potential to be a primary contributor to this agency problem (EIA (2012)).

A reduction in the incentive to conserve may lead to energy overconsumption along multiple dimensions. In the commercial sector, many buildings are over-cooled in the summer months, leading to an increase in electricity consumption of up to 8 percent (Derrible and Reeder (2015)). Equipment and electronics usage may also increase if there are poor incentives to conserve. Sanchez et al. (2007) find that office equipment and electronics - such as computers, personal space heaters and fans - account for up to 20 percent of annual building-level electricity consumption. Basarir (2010) notes that, in retail settings, open doors increase consumption by up to 9 percent. 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), who find that energy consumption by tenants who pay their own energy bills is 20 percent lower compared to owner-paid units. However, as noted by the authors, this estimate reflects the effect of both contract type itself, and selection into contract type and buildings based on preferences for energy services. In the residential sector, the current consensus is that the split incentive effect on aggregate consumption is likely modest. Levinson and Niemann (2004) find that energy bills are 0.7 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.[2] 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 to their electricity bills (see, for example, Jessoe et al. (2014) and Ito (2014)). This is potentially a result of the relatively small financial rewards at stake.

We evaluate our research questions within the jurisdiction of United Illuminating (UI), an investor-owned electric utility in Connecticut servicing customers across 17 counties. Figure 1 shows its service territory. Most Connecticut commercial customers heat their units with natural gas or fuel oil rather than electricity (EIA (2012)), leading us to hypothesize that electricity use will be most responsive to weather conditions in the summer months, when air-conditioning use is high.

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 tenant's individual electricity use 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

[2] Another dimension to the principal-agent problem is less than efficient turnover from oil-fired to gas-fired boilers for residential heating in the northeastern U.S (Myers (2014)). This outcome is consistent with asymmetric information over heating costs when tenants pay for heat. Inefficient turnover led to 37 percent higher annual heating costs in the 1990-2009 period.

buildings initially constructed with sub-meters in place could charge individual tenants for energy consumption.[3] In all other buildings electricity consumption was monitored at the building level, and thus tenants signed owner-paid 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 were still able to choose buildings based on electricity contract type, doing so limited their choice set to buildings retrofitted with a sub-meter at the time of construction, an implicit cost.

In 2013, new legislation passed by the Connecticut General Assembly eliminated the sub-metering prohibition (Hartford Business Journal (2013)). While we cannot directly test the effect of this change on electricity use due to the fact that it post-dates our electricity billing sample, 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.

3 Data

We combine three data sets to form a panel of of 40,962 observations from 1,126 firms. The first source is monthly billing data provided by UI that reports account-level monthly electricity consumption (in kWh), peak monthly throughput (in kW), and monthly 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 year of construction, number of stories and building size. Third, we obtained average daily temperature data from the National Oceanic and Atmospheric Administration (NOAA).

Table 1 presents sample summary statistics on usage, location and industry by contract type.

[3]Several states have historically banned utility sub-metering, primarily for consumer protection reasons. The main concern has been that owners would overcharge tenants for sub-metering services. States that have banned sub-metering include California, New Jersey, Massachusetts, and New York (Allen et al. (2007), NJAA (2005), Cross (1996)). Other states such as Arizona and Georgia have allowed sub-metering to occur in a legal gray zone, leaving owners open to lawsuits for charging sub-metering fees (Treitler (2000)).

The predominant share of accounts are located in office buildings (72 percent), followed by industrial buildings (22 percent), and then by retail and flex buildings, which combine office and retail functions (6 percent). In our sample, about 84 percent 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 distributed regionally, with about 30 percent of observations in central cities, and the rest located in more suburban areas.

In our empirical work, weather is measured as the number of cooling degree days (CDD) and heating degree days (HDD) 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 CDD and HDD at each weather station. CDD are obtained by subtracting 65 from the average Fahrenheit temperature on a given day with temperatures above 65, while HDD are obtained by subtracting the average Fahrenheit temperature on a given day from 65 on days with temperatures below 65.[4] These daily weather station measures are used to compute daily zip code level weather. We use inverse distance weighting relative to zip centroids, and then sum within a 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 billing period to arrive at average daily CDD and HDD by billing month.

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 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 our weather variable 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

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

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 billing cycles.

The assignment of billing cycles based on geography raises the possibility that they may be correlated with weather and contract type. We investigate this by testing if a systematic relationship between bill cycle and weather exists. A regression of weather on bill cycle shows that that the sixteen billing cycles are neither jointly nor individually significant in explaining cooling degree days or heating degree days.[5] Nevertheless, our empirical approach explicitly addresses this concern by conditioning on billing cycle.

4. Empirical Framework

Earlier empirical work on split incentives in the commercial energy setting assumes that the mechanism by which firms are assigned to owner- or tenant-paid utility contracts is independent of fixed firm characteristics. We relax this assumption and control for the possibility that firms may select into contract type based on contract attributes. Our research design focuses on one margin where a split incentives problem may be observed - cooling during summer months - and our empirical approach exploits within-firm variation in CDD that is generated from the staggering of billing cycles. This allows us to test if the relationship between temperature and electricity use varies systematically across utility-included and excluded contract types.

In this section, we begin by describing a simple levels comparison of electricity use across firms on owner- and tenant-paid contracts, and show that this approach will likely lead to biased estimates of the principal-agent problem. Next, we detail the empirical approaches that we deploy, the coefficient estimates that these retrieve, the identifying assumptions upon which our empirical approach hinges, and two robustness tests that we implement.

4.1 Average Treatment Effects: Levels Comparison

To examine the split incentives problem, we begin by comparing overall electricity use across firms on owner- and tenant-paid contracts conditional on a number of rich time controls using OLS,

[5] See Appendix section A.1.

$$Y_{it} = \alpha + \beta_1 C_{zt} + \beta_2 H_{zt} + \theta T_i + \eta_i t + \gamma_t + \varepsilon_{it} \tag{1}$$

The outcome variable is the natural log of electricity use for firm i in billing month t. The regressor of interest, T_i, is an indicator variable that takes on a value of 1 if firm i is on a utilities-excluded or tenant-pays contract, and 0 if it is on a utilities-included or owner-pays contract. The variables C_{zt} and H_{zt} are average daily cooling and heating degree days for a firm assigned to billing month t and located in zip code z. We further condition on billing month fixed effects, denoted by γ_t, and firm-specific time trends η_i.

Our coefficient of interest, θ, will reflect the average effect of contract type on monthly electricity use if assignment to a tenant-paid or owner-paid contract is independent of potential outcomes. In our setting, this identifying assumption seems untenable, since the mechanism by which firms and buildings are assigned to contract type is likely correlated with fixed firm or building attributes that also determine electricity use. Tenants may sort into contract type based on electricity use, the elasticity of their electricity demand, or firm-specific attributes. Another possibility is that the presence of sub-meters in a building, and hence the ability for owners to implement tenant-paid contracts, may be co-determined with other fixed building attributes. In our setting, the decision to construct a building with or without sub-meters may coincide with other construction decisions such as insulation or window quality that affect electricity use. For these reasons, buildings and firms on tenant-paid contracts likely differ from those on owner-paid contracts in ways that affect electricity use. Failure to account for selection into contract type may result in a biased estimate of θ.

To empirically explore whether selection on fixed firm and building attributes may confound the estimation of equation (1), we compare firms on owner- and tenant-paid contracts across a number of observables that we hypothesize may be related to contract type. Tables 1 and 2 report mean characteristics for firms on tenant- and owner-paid contracts, as well as the t-statistic associated with the difference in means. Motivated by empirical specifications that focus on the principal-agent problem among all firms and only the largest electricity users, we present these comparisons for all firms in our sample, Table 1, and firms in the top electricity consumption decile, Table 2. As shown in Table 1, when we focus on the full sample, the covariates are balanced along the rich set of covariates we observe. However, a comparison of means across the top decile of electricity users reveals that firms on owner- and tenant-paid contracts differ along a number of observables, including building height and industry type. These balance statistics cast doubt on an empirical approach that relies on a levels comparison in electricity use across firms on different contracts, and lead us to forgo the formal estimation of equation (1).

4.2 Average Treatment Effects: Temperature Gradient

We propose an empirical approach that controls for the possibility that firms and buildings on owner- and tenant-paid contracts may be systematically different in fixed attributes that also affect electricity use. We begin with the hypothesis that if a split incentives problem exists, then it should be observed in differences in cooling across owner- and tenant-paid contracts. We test this hypothesis by evaluating how electricity use differs in response to a 1 cooling degree day increase across firms on an owner- versus tenant-paid contract, controlling for firm fixed effects and weather.

To evaluate the differential effect of a CDD on electricity use across contract type, we estimate a fixed effects model using OLS,

$$Y_{it} = \beta_1 C_{zt} + \beta_2 H_{zt} + \theta_1 T_i \times C_{zt} + \theta_2 T_i \times H_{zt} + L_t + \eta_i t + \gamma_t + \gamma_i + \varepsilon_{it} \tag{2}$$

In this specification, the indicator variable for whether tenant i pays its own electric bill is interacted with each of the weather variables, $T_i \times C_{zt}$ and $T_i \times H_{zt}$. Importantly, this estimating equation conditions on account fixed effects, γ_i. This allows us to control for all fixed firm and building characteristics including those that affect electricity use and may systematically differ across contract type. We also condition on bill length, L_t, defined as the number of days in a billing month, to account for differences in weather attributable to variation in bill length across billing months.

The coefficient, θ_1, reflects the differential effect of temperature increases on electricity use across firms on owner- and tenant-paid contracts. A natural interpretation of θ_1 is the change in demand for air conditioning across contract type in response to warmer temperatures, holding constant the existing building stock. To estimate this treatment effect, we exploit variation in

CDD generated from the staggering of billing cycles, and compare how a firm on an owner-versus tenant-paid contract responds to this variation netting out fixed firm characteristics. This approach allows us to account for fixed building and firm attributes systematically correlated with contract type and electricity use.

Nevertheless, identification of the treatment effect still rests on a key assumption: the response of electricity use to CDD differs only by unobservables uncorrelated with contract type. When compared to the levels regression in equation (1), the requirements for identification are less onerous. This is because equation (2) allows for selection into contract type based on fixed unobservables. A violation would only occur if attributes systematically correlated with contract type also exhibit a temperature-dependent impact on electricity use. A second advantage of our approach is that it explicitly accounts for the possibility that the electricity response to temperature shocks differs significantly across fixed building attributes (Novan et al. (2017)). Our empirical approach only breaks down if fixed building attributes that affect electricity use in a temperature-dependent way are also systematically correlated with contract type. In our setting, this would occur if, for example, building age was systematically correlated with contract type, and the electricity response to temperature differed across building vintage.

To examine the plausibility of our main identifying assumption, we augment equation (2) to account for the possibility that building attributes that differ systematically across contract type may also impact electricity use along a temperature gradient. Our main estimating equation thus conditions on interactions between weather and a number of building and firm attributes,

$$Y_{it} = \beta_1 C_{zt} + \beta_2 H_{zt} + \theta_1 T_i \times C_{zt} + \theta_2 T_i \times H_{zt} + \boldsymbol{\psi} \boldsymbol{X_i} \times [C_{zt}, H_{zt}] + L_t + \eta_i t + \gamma_t + \gamma_i + \varepsilon_{it} \quad (3)$$

The term $\boldsymbol{\psi}\boldsymbol{X_i} \times [C_{zt}, H_{zt}]$, denotes a vector of building and firm attributes interacted with heating and cooling degree days, where $\boldsymbol{X_i}$ includes indicator variables for building type (retail, office, etc.), firm NAICS code, quartile of building vintage and building stories.[6]

Our testable hypothesis is that if building attributes confound the temperature response gradient then our coefficient estimate on contract type, θ_1, will be sensitive to the inclusion of interactions between temperature and building/firm covariates. If the coefficient estimate remains

[6] We show in Appendix Table A2 that the results are not sensitive to how the characteristic variables are specified, e.g. in levels, quartile dummies, tertile dummies etc.

unchanged after conditioning on these interaction terms, then this provides evidence to support our main identifying assumption.

4.3 Conditional Average Treatment Effects: Temperature Gradient

A central focus of this paper is whether the size of the split incentives problem varies substantially across firms. One form of heterogeneity in the response to contract type may arise based on electricity use, since relatively larger users of electricity may devote a larger share of their budget to electricity expenditures. To empirically examine this form of heterogeneity, we estimate conditional average treatment effects for firms in different deciles of average monthly electricity use. To implement this, we augment equation (3) and estimate,

$$\begin{aligned} Y_{it} = \boldsymbol{\beta_{1d}}(C_{zt} \times \mathbb{1}_{id}) + \boldsymbol{\beta_{2d}}(H_{zt} \times \mathbb{1}_{id}) + \boldsymbol{\theta_{1d}}(T_i \times C_{zt} \times \mathbb{1}_{id}) + \boldsymbol{\theta_{2d}}(T_i \times H_{zt} \times \mathbb{1}_{id}) \\ + \boldsymbol{\psi_d X_i} \times [C_{zt} \times \mathbb{1}_{id}, H_{zt} \times \mathbb{1}_{id}] + L_t + \eta_i t + \gamma_t + \gamma_i + \varepsilon_{it} \end{aligned} \quad (4)$$

This estimating equation now includes a vector of indicator variables denoted by $\mathbb{1}_{id}$ that are set equal to 1 if tenant i has electricity demand in decile d (i.e. $d = \{1, ..., 10\}$), and zero otherwise. These indicator variables are interacted with the weather variables, and the treatment effect of interest. This allows to us to separately estimate, for each decile of electricity use, the differential effect of a CDD on demand for electricity across contract type.

4.4 Robustness

To examine the plausibility of our main identifying assumption, we implement two novel robustness tests. The first makes use of a regulatory change allowing buildings to switch contract type and tests if selection remains an empirical concern. The second applies a new technique proposed by Oster (2016) to bound our estimated treatment effects.

Our first robustness test takes advantage of a policy change to sub-metering regulations. Within our sample period, a ban on sub-metering retrofits in Connecticut made selection by customers and building owners along contract type very costly, if not impossible. For example, customers desiring attributes of a centrally-metered building may have preferred to pay their own electricity, and landlords may have preferred to offer tenant-paid energy 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 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 which buildings switched and to directly examine whether controlling for them changes our baseline results.[7] Under the null hypothesis of "no selection," our estimated treatment effect should be unchanged after conditioning on the identity of firms switching contract types by interacting indicator variables for these "switchers" with CDD and HDD.

Our second test 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 this is the case, movements in the coefficient of interest and R-squared levels from the inclusion of control variables inform us about selection on unobservables. Building on Altonji et al. (2005), Oster (2016) points out that under the plausible assumption that observable controls share covariance properties with unobservable variables, omitted variable bias is proportional to coefficient movements, but only if these movements are scaled by changes in R-squared. An ideal scenario in this context is one in which the treatment coefficient of interest changes very little as new covariates are added, and the regression R^2 approaches its maximal possible value, after accounting for measurement error (Gonzalez and Miguel (2015)). In this case, the large R^2 suggests there is little variation remaining to bias the coefficient. The Oster approach yields a consistent estimator for the bias-adjusted coefficient of interest, or an identified set formed by the treatment effect in the fully controlled regression, and the bias-adjusted effect. We retrieve the Oster bounded set in a post-estimation procedure and

[7] Roughly six percent of customers switched contract types by early 2015, with 34 owners moving to a tenant-paid contract and 31 transitioning to an owner-paid contract. Switches to owner-paid contracting were not limited prior to the sub-metering policy change, and there are several reasons why owners may switch to owner-paid contracting (see for example Levinson and Niemann (2004)). Importantly, these switches may also be related to the policy change itself - owners who wish to upgrade or reconfigure their building metering infrastructure may need to master-meter tenants for a transition period. We control for both types of switches in our empirical specifications.

present it in our discussion of the results.

5 Results and Discussion

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 one-degree bins, across both contract types, for the bottom nine deciles 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 3 presents our formal regression results. Column (1) shows the effect from the estimation of equation (2), 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 and billing-month fixed effects and firm-specific time trends. When looking across all firms, we find there is no difference in the effect of weather shocks on consumption across contract type. In the remainder of Table 3, we report results that include tenant-paid contract interactions with CDD and HDD for each consumption decile. Column (2) reports results from the estimation of the conditional average treatment effects analog of equation (2), and columns (3)-(5), which examine the robustness of this result to potential confounding factors, report results from the estimation of equation (4). Column (3) conditions on the interaction of CDD and HDD with building and industry type; column (4) adds interactions of CDD and HDD with building vintage quartiles; and column (5) adds controls for the differential effect of temperature shocks among switchers.[8]

[8]In Table A2, we also include building storey interactions with cooling and heating degree days; the results are

Our results indicate that a split incentives 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. Focusing on our preferred specification in column (5), 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. This translates into about a 3 percent decrease in electricity use among the top decile of users. 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 use but only during the hot summer months. In the summer months, switching from an owner to a tenant-paid contract would reduce monthly electricity consumption by up to 14 percent. The summer response is consistent with a framework in which demand for electric air conditioning during these hot months drives the divergence in the temperature response gradient 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 of roughly 19,000 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 use.

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qualitatively unchanged and the point estimate on our variable of interest increases. Table A2 also shows that our treatment effect is not sensitive to the functional form of the building characteristic controls.

[9]The coefficients on HDD (not reported) are not statistically significant. Since most firms in Connecticut use natural gas or fuel oil for heating, this is not surprising.

We also estimate the effect of contract type on electricity expenditure by estimating our preferred conditional average treatment effects specification with log monthly bill as the dependent variable; results are shown in column (6) of Table 3. For the top decile of electricity consumers, the estimated treatment effect is a 1.2 percent decrease in the monthly bill per CDD. The value of total bill savings among these high consumers is approximately $310 per summer month. On average, this represents a 10 percent reduction in electricity expenditure.

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 before and after the inclusion of covariates; (ii) R-squared values before and after the inclusion of covariates; and (iii) the maximum theoretically possible R-squared, namely from a regression on consumption and all possible observable and unobservable controls. This maximum R-squared may be less than 1 if there is measurement error.

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), Altonji et al. (2005)). Table 4 reports the identified set estimates from two different specifications with log usage and log bill as the dependent variables, respectively, corresponding to the fully controlled specifications reported in columns (5) and (6) of Table 3.[10] As shown in this table, we continue to detect a split incentives effect after accounting for any remaining selection on unobservables. A tenant-paid contract induces at minimum monthly electricity and bill savings of 0.7 and 0.6 percent per CDD, respectively.[11]

5.1 Generalizability

There are roughly 18 million commercial electricity customers in the U.S. and 5.6 million commercial buildings ((EIA (2017), EIA (2012)). In this section, we explore the similarity of the subpopulation under study here to the full population of commercial sector tenanted buildings in the U.S. Understanding if our estimates apply to the broader population of large commercial users

[10]These set estimates 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)).

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

provides insights into the potential energy savings from restructuring electricity contracts from owner- to tenant-pay. To demonstrate the broader relevance of our results, we proceed in three steps. First, we make use of a representative data set of national commercial building attributes to show that, along important observables, the data source used in our analysis is representative of building attributes throughout the U.S. Second, we focus exclusively on the database used in our analysis, and illustrate that the distribution of attributes for commercial buildings in Connecticut is similar to those in the broader U.S. Third, we then compare contract types and energy intensity in commercial buildings in Connecticut to those across the U.S. We use these contract type statistics in Section 5.2 to estimate the energy savings implied by our treatment effect.

In the first step, we demonstrate that the building database used in our analysis is a representative sample of building attributes in the U.S. Our empirical sample uses data on contract type and building attributes collected from the CoStar group. An advantage of the data collected by the CoStar group is that it includes buildings throughout the U.S., totaling about 97 percent of tenanted buildings. We compare three important building characteristics in the CoStar dataset - building height, age and size - to the Energy Information Administration's Commercial Building Energy Consumption Survey (CBECS), a nationally representative data set on attributes in both owner and tenant occupied commercial buildings. The CBECS and CoStar datasets are very similar in building height and vintage. While the average CoStar building is larger than the CBECS average, this may be representative of the larger size of leased buildings compared to owner-occupied buildings (EIA (2012)). These similarities in observables, along with the fact that the CoStar database is reflective of leased commercial buildings in the U.S., lends confidence to the national representativeness of the CoStar data.

Second, we show that within the CoStar data there is strong overlapping support in the distributions of measurable building characteristics between Connecticut and the rest of the United States. The overlapping support of building characteristics can be seen in Figure 4. Ideally, we would compare attributes of buildings in the top 10th percentile of electricity usage in Connecticut to those in the U.S. This is not feasible since CoStar does not collect electricity use as a variable. Instead we display the full distribution for both Connecticut and the U.S. of building attributes that we hypothesize are highly correlated with electricity use: square feet, number of stories, and year of construction. For all three variables, significant overlap exists, despite some apparent differences (e.g. Connecticut has a lower proportion of very small buildings). As we discuss below, differences between the Connecticut sample and the broader population imply that the commercial split incentives problem is potentially even larger in the rest of the U.S. than in Connecticut.

Finally, comparing the composition of contract types and energy intensity in Connecticut to the rest of the U.S. once again leads to the conclusion that the split incentive problem is likely at least as large outside of Connecticut as it is within Connecticut. Approximately 34 percent of commercial, non-government floorspace in New England is leased, as compared to 39 percent nationwide (EIA (2012)).[12] The CoStar database reports contract type for commercial lessees nationwide, differentiating between contracts that transmit price incentives to tenants and those that do not. In our Connecticut sample, about 15 percent of commercial lessees are on owner-pay contracts, as compared to 25 percent nationwide.[13] With respect to energy intensity, New England is the least energy-intense region in the nation when measured by kWh per square foot of commercial building space (EIA (2012)). When we condition on buildings in which owners pay for electricity, New England is still well below the national average: 11.6 kWh per square foot in New England versus 14.4 nationwide.

Proportionally, less commercial floorspace is rented in New England than nationwide; a higher proportion of commercial renters are on owner-pay contracts in the rest of the U.S.; and the energy intensity per commercial square foot is higher in regions outside of New England. Thus in terms of the magnitude of the potential split incentives problem in the commercial segment, it is likely to be larger per square foot of commercial building space in the rest of the country than it is in Connecticut.

[12] EIA's Commercial Building Energy Consumption Survey (EIA (2012)) publicly reports this variable at the regional level, rather than by state.

[13] The nationwide figure is even larger if we include contracts with a prorated utility payment for all building occupants, whereby tenants pay a weighted average of the building's utility bill based on the square feet occupied. In this contractual arrangement, tenants do not pay for the marginal cost of their energy use and large consumers benefit by paying less than their share of utilities. Conservatively, we categorize these as 'owner-paid' in our paper, though only about 3 percent of tenants are on a prorated contract in our sample. Nationwide, about 20 percent of tenant contracts include a prorated utility payment. In Section 5.2 we treat these figures under the most conservative assumptions.

5.2 Quantifying Benefits from Aligning Split Incentives

Under conservative assumptions, restructuring rental contracts for the largest ten percent of commercial firms nationwide would produce energy savings roughly three times those achieved from restructuring rental contracts for all residential users who don't pay for their utilities. This conclusion is derived from the following calculation. There are 130 million residential electricity customers in the U.S., of whom 10.4 million rent dwellings with utilities included (EIA (2009)). Assuming they conserve 0.7 percent of their electricity when exposed to a non-zero price (Levinson and Niemann (2004)), total residential savings are 142 million kWh per year. By comparison, there are approximately 18 million commercial sector electric customers in the U.S. (EIA (2017)), 39 percent of which rent their building space (based on the share of tenanted buildings in the U.S. in EIA (2012)). Suppose 25 percent of those (1.74 million) have an owner-paid utilities contract. The top consumption decile, 174,000 customers, save a total of 411 gigawatt-hours per year (1.4 percent based on our preferred empirical estimates) from a switch to tenant-pay contracts. This amounts to 289 percent percent of the residential sector analog. Under much more conservative assumptions, this number falls to 177 gigawatt-hours per year, or 125 percent of the residential sector analog.[14]

Addressing the commercial split incentives problem has relatively high benefit-to-cost. Using data on the costs of sub-metering, we estimate 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 Research (2012), White (2012), Millstein (2008)). Given the 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 average of the sub-meter cost ranges cited above), the payback period is less than one year, even after allowing for installation costs. This is well below the payback threshold for most firms' energy conservation investments (Anderson

[14]We reduce the fraction of renters from 39 percent to 36 percent to reflect the share of tenanted floor space, rather than the share of tenanted buildings (EIA (2012)), use the average electricity use across all large firms (not just those on owner-pay contracts, who use more electricity), and adjust our treatment effect estimate down by one standard deviation. These changes are multiplicative and thus result in an extremely conservative estimate. As mentioned in the previous section, it is likely that the base case comparison to the residential sector understates the relevance of our results to the U.S. commercial sector as a whole, so the conservative estimate should be interpreted as a lower bound.

and Newell (2004)).[15] With a unit- or firm-level sub-meter cost of \$625, a cost which would be incurred up-front, and an average annual treatment effect of 19,000 kWh saved among high consuming firms, the cost effectiveness is 3.3 cents per kWh after the first year, 1.6 cents per kWh after two years, and 1.1 cents after 3 years, assuming the annual electricity savings persist at the same level.

To calculate the reduction in external damages from a switch to tenant-paid contracts, we convert energy savings into avoided CO_2 and $PM_{2.5}$ emissions, and then monetize the reduction in emissions.[16] To quantify CO_2 we use the Environmental Protection Agency's eGRID database which provides 2009 emission rates for the New England subregion, measured as tons emitted per MWh of electricity produced.[17] The energy savings translate into CO_2 savings of between 615 to 1200 thousand tons per year. To give a sense of scale, this is between 3.3 to 6.6 times the average annual savings achieved from yearly Weatherization Assistance Program (WAP) retrofits.[18] The $PM_{2.5}$ emission rates estimate is obtained from Connors et al. (2005). Marginal damage estimates for $PM_{2.5}$ come from Muller and Mendelsohn (2007), and marginal CO_2 damages are from IWGSCC (2015).

The upper and lower bound estimates for avoided pollution-related external costs are presented in Table 5. As shown in columns (1) and (2), the per firm value of avoided damages ranges from \$102 to \$204. In columns (3) and (4) we add to this the estimated bill savings of \$677 to \$1265 per firm-year. Using this measure, the annual firm-level social benefit of switching from an owner- to tenant-paid contract is between \$779 and \$1469. Finally, in columns (5) and (6) we measure the value of the energy savings using the avoided marginal cost of electricity (in place of bill savings). We use this approach to net out fixed costs. Fixed costs are not avoided costs in this setting,

[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.

[16] We do not include damages from NO_x and SO_2 emissions, given regional and federal regulations in place during our sample time frame. Assuming the emissions caps for these regulations were binding, a reduction in electricity consumption would not reduce aggregate emissions but reallocate them to a different source. While CO_2 emissions were also regulated through the Regional Greenhouse Gas Initiative from 2009 onwards, the early phase of this program did not have a binding cap (CRS (2017)).

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

[18] 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.

since they will be recovered by the utility from other customers under the cost-plus regulatory structure in Connecticut. Our measure of avoided marginal cost is the average hourly locational marginal price for Connecticut over the sample period, \$59.42.[19] Total social benefits using avoided marginal costs are between \$676 and \$1346. Given that the average cost of a sub-meter is \$625, sub-metering retrofits are likely net beneficial from a social perspective.

5.3 The Non-Response of Most Commercial Firms

While we estimate that contract type has a sizable effect on electricity use for the largest firms, one unanswered question is why the remaining 90 percent 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)). In this section, we provide evidence for this hypothesis by performing a coarse cost-benefit analysis for a common energy-saving behavioral change. 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. Overcooling and overheating are common in office buildings, and some occupants' behavioral responses, such as running personal heaters or fans, 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 4,300 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, 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.

[19] Our data source is the New England Independent System Operator (NE-ISO), www.iso-ne.com.

One possibility is (potentially rational) inattention leading to unresponsiveness among commercial firms (Jessoe and Rapson (2015)). 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 to 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 forgo likely represent a 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)).

6. Conclusion

We measure the "split incentive" effect of tenancy contract type using a unique empirical setting and dataset of tenancy contracts and energy use among commercial sector clients. Our empirical framework compares how temperature shocks impact electricity consumption across firms on owner- and tenant-paid contracts. Importantly, it helps us to overcome the well-known empirical challenge of separately identifying the split incentives problem from selection on fixed attributes.

Our approach consists of three steps to probe and address the main identification challenge: selection on unobservables that affect electricity use along a temperature gradient. We allow for a heterogeneous temperature response gradient along several dimensions by including interactions between temperature and building attributes that may be correlated with energy consumption, testing for selection by taking advantage of a state-level change in metering regulations, and accounting for any potential remaining correlations between unobservable characteristics and the treatment using the Oster (2016) identified set approach.

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 since the bill savings from conservation behavior are relatively small across most of the consumption distribution. Hence, they are likely not large enough to justify energy efficiency investments or behavioral changes.

The result implies a strong policy 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 percent 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 a 3 percent saving for firms in the top consumption decile. These savings generate annual external benefits between $102 and $204. The payback period from sub-metering and switching to a tenant-paid contract is less than one year, and a targeted policy of sub-metering and tenant-paid contract promotion would likely be a net beneficial addition to the portfolio of energy conservation and greenhouse gas mitigation strategies utilized by policymakers.

Several features of our findings lead us to have conviction about the potential importance of commercial split incentives in electricity. The commercial split incentives problem is large and likely even more important in the rest of the U.S. than in Connecticut, due to the higher prevalence of leased space and owner-pay contracts. If our sample is representative, then the public and private benefits both independently provide an efficiency case for facilitating sub-metering and tenant-pay contracts among top consumers. Moreover, if sub-metering occurs after the building is constructed, features of the building envelope are predetermined and thus less likely to be exposed to underinvestment in energy efficiency that may arise from tenant-pay contracts. Finally, the sheer size of large commercial electricity customers distributes the fixed cost per kWh conserved due to sub-metering much more efficiently than can occur in the residential case. While it would of course be beneficial to run a large-scale randomized trial to reduce the possibility of erroneous conclusions, we view a strong case for policy action or, at the very least, a concerted effort to resolve uncertainties about the policy case.

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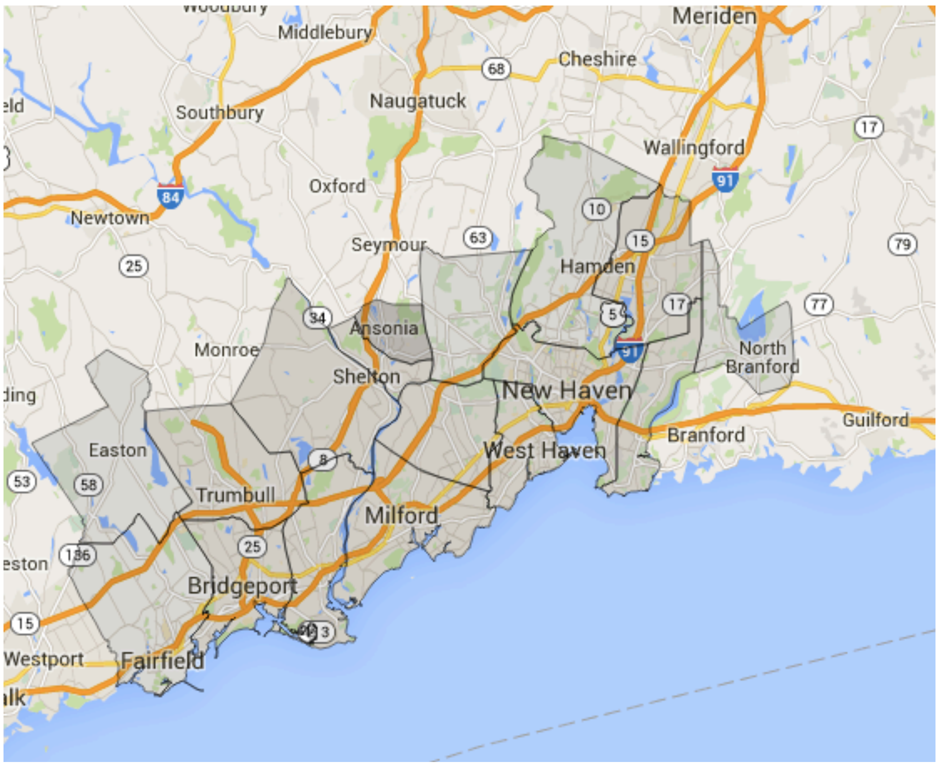
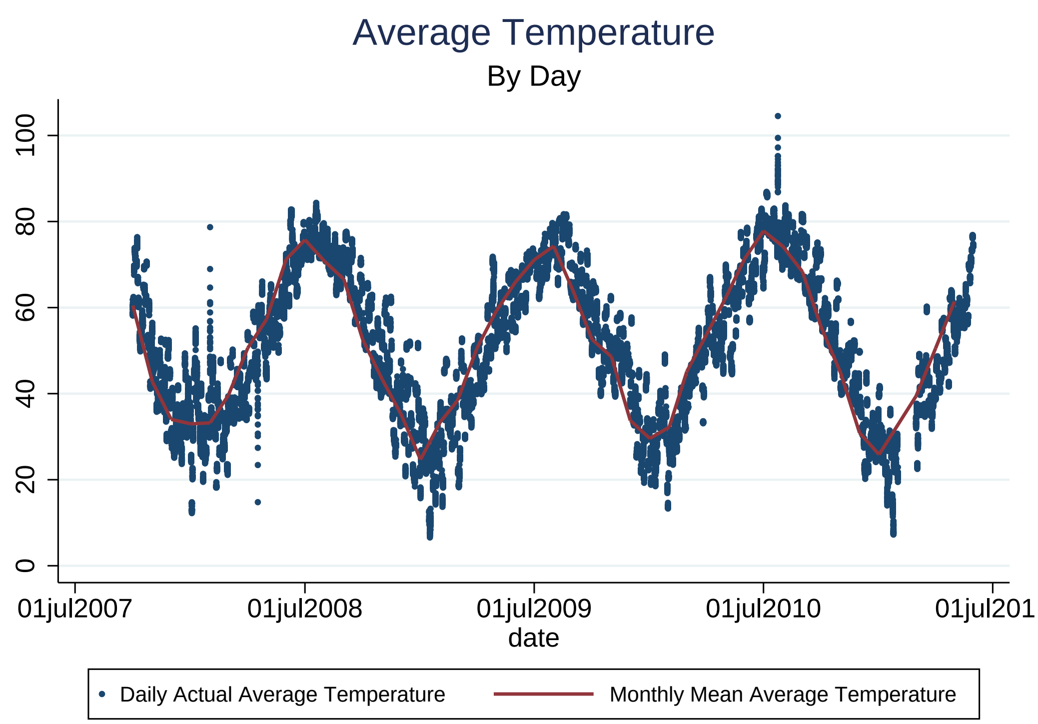
Figure 1: UI Territory



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

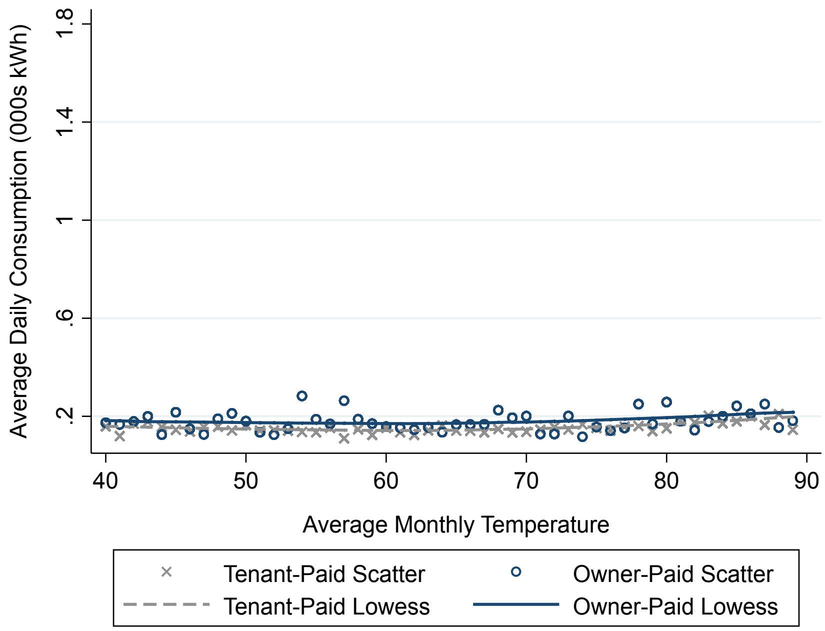
Figure 2: Weather Data Variation



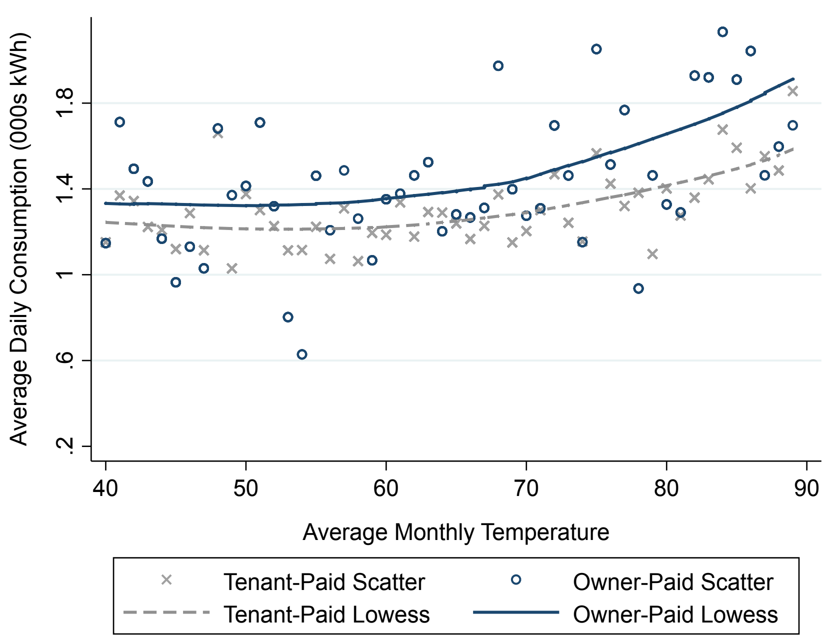
Notes: Average daily temperature in UI's service territory between October 2007 and May 2011, at the zip code level. Despite the relatively small region, there is visible cross-sectional variation in daily temperatures, with summer temperatures varying between 5 to 10 degrees across zip codes. Temperature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

Figure 3: Consumption By Contract Type

(a) Bottom Nine Deciles



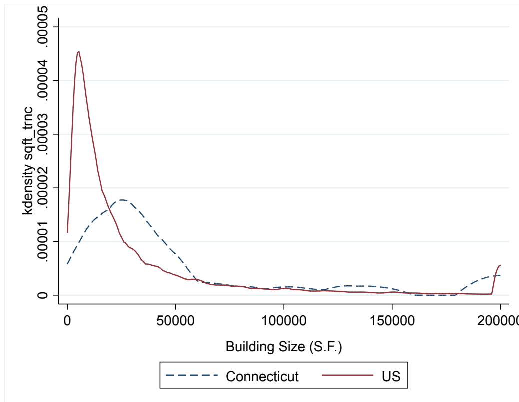
(b) Highest Consumption Decile



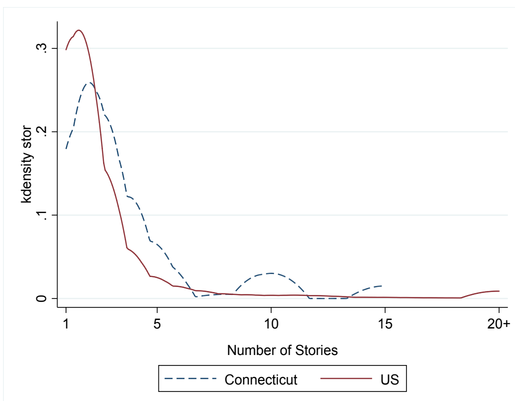
Notes: Each scatter plot presents monthly electricity consumption against average temperature within 1-degree bins, for the bottom nine decile of firms in panel (a), and the top consumption decile in panel (b). The observations are color-coded by contract type, in both the bottom nine deciles (panel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

Figure 4: Support of Building Characteristics in Connecticut vs. U.S.

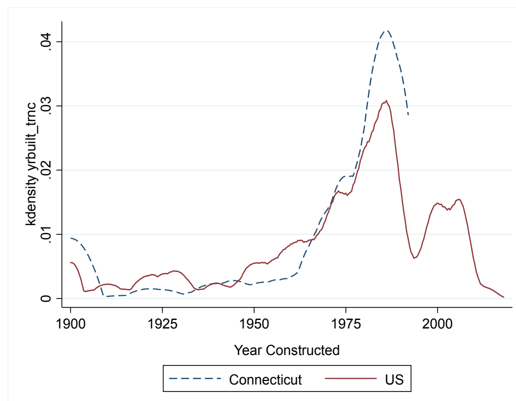
(a) Building Size



(b) Building Stories



(c) Year Constructed



Notes: The Figure shows the overlapping support of building size, stories and year of construction for Connecticut and U.S. buildings.

Table 1: Summary statistics and covariate balance in full sample

	All Firms				
	Tenant-Paid		Owner-Paid		t-Statistic
	Mean	St. Dev.	Mean	St. Dev.	
kW	27.3	42.9	33.5	61.4	0.42
kWh (000s)	7.7	13.8	9.0	17.1	0.31
Bill ($)	627	999	720	1220	0.31
Bill Length	30.3	1.3	30.4	1.3	0.30
Building S.F. (000s)	57.2	59.7	66.8	93.6	0.43
Year Built	1974	26	1968	33	0.76
Building Stories	2.6	1.6	3.4	3.1	1.09
Industry	0.12	0.33	0.10	0.31	0.25
Trade, Accommodation	0.15	0.36	0.12	0.33	0.35
Finance, Real Estate, Management	0.47	0.36	0.55	0.50	0.66
Education, Health, Pub. Admin.	0.19	0.36	0.18	0.38	0.11
Entertainment, Recreation, Services	0.07	0.36	0.05	0.21	0.33
North	0.40	0.49	0.36	0.48	0.33
South	0.60	0.49	0.64	0.48	0.33
City	0.30	0.46	0.31	0.46	0.09
Observations	34,304		6,658		
Firms	948		178		

Notes: The table shows the mean and standard deviations for the observed covariates, for tenant-paid and owner-paid contracts, respectively. The last column shows the value of the t-statistic for the null hypothesis of equal means between the two contract types.

Table 2: Summary statistics and covariate balance in top consumption decile

	Top Decile Firms				
	Tenant-Paid		Owner-Paid		t-Statistic
	Mean	St. Dev.	Mean	St. Dev.	
kW	132.4	71.2	164.2	120.9	1.11
kWh (000s)	40.6	24.1	44.5	34.1	0.47
Bill ($)	3002	1759	3276	2403	0.47
Bill Length	30.4	1.3	30.4	1.3	0.03
Building S.F. (000s)	86.8	79.7	144.9	146.4	1.68
Year Built	1978	19	1973	24	0.85
Building Stories	3.0	2.4	6.1	5.1	2.61*
Industry	0.22	0.41	0.18	0.39	0.40
Trade, Accommodation	0.09	0.28	0.04	0.20	0.92
Finance, Real Estate, Management	0.46	0.50	0.77	0.42	2.83*
Education, Health, Pub. Admin.	0.09	0.29	0.00	0.00	2.96*
Entertainment, Recreation, Services	0.15	0.35	0.00	0.00	4.09*
North	0.39	0.49	0.27	0.44	1.06
South	0.61	0.49	0.73	0.44	1.06
City	0.27	0.45	0.40	0.49	1.07
Observations	3,202		703		
Firms	91		19		

Notes: The table shows the mean and standard deviations for the observed covariates, for tenant-paid and owner-paid contracts, respectively. The last column shows the value of the t-statistic for the null hypothesis of equal means between the two contract types. Asterisks indicate a rejection of the null at the 5 percent level of significance.

Table 3: Split Incentive Effect By Consumption Decile

Dependent variable:	Log Usage					Log Bill
	(1)	(2)	(3)	(4)	(5)	(6)
Tenant x CDD	-0.00001					
	(0.00009)					
Tenant x CDD (10th Dec.)		-0.013**	-0.015***	-0.015**	-0.014**	-0.012**
		(0.006)	(0.006)	(0.006)	(0.006)	(0.005)
Tenant x CDD (9th Dec.)		0.001	0.004	0.005	0.005	0.004
		(0.009)	(0.010)	(0.009)	(0.009)	(0.009)
Tenant x CDD (8th Dec.)		-0.001	0.005	0.005	0.004	0.002
		(0.007)	(0.007)	(0.007)	(0.007)	(0.005)
Tenant x CDD (7th Dec.)		-0.004	-0.001	0.003	0.003	0.001
		(0.007)	(0.008)	(0.007)	(0.007)	(0.005)
Tenant x CDD (6th Dec.)		0.010	0.014*	0.011	0.012	0.009*
		(0.008)	(0.007)	(0.007)	(0.007)	(0.005)
Tenant x CDD (5th Dec.)		0.003	0.005	0.005	0.005	0.004
		(0.007)	(0.008)	(0.007)	(0.007)	(0.005)
Tenant x CDD (4th Dec.)		0.009	0.011	0.012	0.012	0.009
		(0.011)	(0.011)	(0.010)	(0.010)	(0.006)
Tenant x CDD (3rd Dec.)		-0.017	-0.017	-0.012	-0.012	-0.006
		(0.014)	(0.014)	(0.013)	(0.013)	(0.008)
Tenant x CDD (2nd Dec.)		0.005	0.004	0.006	0.006	0.006
		(0.010)	(0.010)	(0.009)	(0.010)	(0.005)
Tenant x CDD (1st Dec.)		-0.010	-0.009	-0.009	-0.009	-0.002
		(0.012)	(0.012)	(0.011)	(0.012)	(0.007)
Account & Time F.E.s, Acct. Trend	YES	YES	YES	YES	YES	YES
Characteristics Interactions	NO	NO	YES	YES	YES	YES
Characteristics Interactions w/ Year-Built	NO	NO	NO	YES	YES	YES
Switchers Controls	NO	NO	NO	NO	YES	YES
Observations	40,962	40,962	40,962	40,962	40,962	40,962
Accounts	1,126	1,126	1,126	1,126	1,126	1,126
R-squared (within)	0.067	0.076	0.088	0.093	0.093	0.26

Notes: The dependent variable in columns (1-5) is the natural log of electricity use in a billing month, and in column (6) it is the natural log of the electricity bill in a billing month. Results are reported from an OLS regression. Column (1) presents results without decile interactions, and columns (2)-(6) include results across consumption deciles. Additional controls included in all regressions are cooling degree days, heating degree days, and heating degree days interacted with contract type. Column (3) further conditions on cooling and heating degree days interacted with building type and NAICS code dummies. Column (4) adds interactions of quartile of year-built with cooling and heating degree days. Column (5) also includes switchers dummies interacted with cooling and heating degree days. Standard errors clustered at the building level are in parentheses, ***p<0.01, ** p<0.05, * p<0.1.

Table 4: Oster Bounds for Monthly Usage and Bill

Log Usage	
	Identified Set Estimate
Lower Bound	-0.014
Upper Bound	-0.007
Log Bill	
	Identified Set Estimate
Lower Bound	-0.012
Upper Bound	-0.006

Notes: The Oster bounds present an identified set of treatment effect coefficients (interpreted as savings per average daily CDD) 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.

Table 5: External Benefits and the Value of Energy Savings Per Firm

	External Benefits		External + Value of Savings (Billed)		External + Value of Savings (Marginal Cost)	
	Low $	High $	Low $	High $	Low $	High $
	(1)	(2)	(3)	(4)	(5)	(6)
$PM_{2.5}$	0.38	0.76	677	1266	574	1143
CO_2	101.95	202.91	779	1468	676	1345
Total	102.33	203.67	779	1469	676	1346

Notes: External Benefits measure the annual per-firm reduction in pollution damages from lower electricity consumption. External + Value of Savings (Billed) measures the sum of the external benefits and the value of the bill savings from contract type, which are the annual bill savings noted in the text ($677-$1487). External + Value of Savings (Marginal Cost) uses the average hourly locational marginal price in Connecticut over the sample period, of $59.42, to value the energy savings. The low and high values are derived from the Oster identified set estimates for electricity savings, discussed in the text.

Appendix

A.1 Bill cycles and weather

We assess whether bill cycle is correlated with the temperature response gradient across contract type by testing for a systematic relationship between bill cycle and weather. In Table A1, we report the results of a regression of weather on bill cycle. As shown, we find that the sixteen billing cycles are neither jointly nor individually significant in explaining cooling degree days or heating degree days.

A.2 Robustness to Alternative Specifications

Our estimated treatment effect is not sensitive to alternative specifications, as shown in Table A2. Column (1) is the fully controlled specification from column (5) of Table 3, augmented with stories quartile dummies interacted with cooling and heating degree days. The point estimate increases and remains statistically significant. In columns (2)-(7) we show that the results are not sensitive to the functional form of the building characteristic controls. The point estimate changes very little when the characteristics are included as is or in the form of tertile, quintile or sextile dummies.

Table A1: Bill Cycle Conditional Independence Assumption

	(1) CDD	(2) CDD 10th Dec.	(3) HDD	(4) HDD 10th Dec.
Bill Cycle 2	-0.037		0.306	
	(0.466)		(1.657)	
Bill Cycle 3	-0.131	0.114	0.298	-0.605
	(0.468)	(0.814)	(1.674)	(2.429)
Bill Cycle 4	0.189	0.433	-0.394	-2.071
	(0.434)	(0.557)	(1.553)	(1.663)
Bill Cycle 5	-0.131	-0.044	0.197	-1.172
	(0.475)	(0.713)	(1.703)	(2.139)
Bill Cycle 6	-0.156	0.154	0.111	-1.000
	(0.527)	(0.814)	(1.886)	(2.429)
Bill Cycle 7	0.050	0.326	0.416	-1.205
	(0.454)	(0.596)	(1.620)	(1.806)
Bill Cycle 8	-0.182	0.184	0.490	-0.594
	(0.499)	(0.620)	(1.775)	(1.865)
Bill Cycle 9	0.470	-0.052	-0.509	-0.911
	(0.501)	(0.632)	(1.796)	(1.936)
Bill Cycle 10	0.621	-0.196	-1.142	-0.966
	(0.509)	(0.686)	(1.833)	(2.160)
Bill Cycle 11	-0.028	0.137	0.646	-1.850
	(0.487)	(0.733)	(1.754)	(2.275)
Bill Cycle 12	-0.061	-0.168	0.170	-0.906
	(0.438)	(0.579)	(1.572)	(1.783)
Bill Cycle 13	0.130	0.006	-0.785	-2.248
	(0.484)	(0.686)	(1.744)	(2.183)
Bill Cycle 14	0.024	-0.151	0.781	-0.751
	(0.448)	(0.586)	(1.600)	(1.783)
Bill Cycle 15	0.157	0.190	0.354	0.208
	(0.569)	(0.709)	(2.003)	(2.128)
Bill Cycle 16	-0.003	0.162	0.466	-1.849
	(0.516)	(0.679)	(1.852)	(2.118)
Constant	2.193***	2.543***	15.408***	16.748***
	(0.377)	(0.451)	(1.358)	(1.335)
Observations	2,479	1,051	2,594	1,270
F test for joint significance	0.471	0.218	0.248	0.245

Notes: Results are reported from an OLS regression of CDD or HDD on bill cycle. The unit of observation is a billing cycle - zip code. Standard erors are reported in parentheses. *** p<0.01; ** p<0.05; * p<0.1

Table A2: Robustness to Alternative Specifications

Dependent variable:	Log Usage						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tenant x CDD (10th Dec.)	-0.016**	-0.014***	-0.015***	-0.017***	-0.017***	-0.016***	-0.016***
	(0.007)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Tenant x CDD (9th Dec.)	0.007	0.004	0.001	0.000	0.000	0.001	0.000
	(0.008)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Tenant x CDD (8th Dec.)	0.006	-0.001	-0.002	-0.003	-0.002	-0.002	-0.001
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Tenant x CDD (7th Dec.)	0.002	-0.007	-0.008	-0.007	-0.007	-0.007	-0.007
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Tenant x CDD (6th Dec.)	0.011	0.010	0.010	0.010	0.010	0.010	0.010
	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)
Tenant x CDD (5th Dec.)	0.006	0.001	-0.000	-0.000	0.000	0.000	0.000
	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Tenant x CDD (4th Dec.)	0.011	0.009	0.009	0.009	0.009	0.009	0.009
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Tenant x CDD (3rd Dec.)	-0.013	-0.018	-0.019	-0.019	-0.019	-0.019	-0.019
	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Tenant x CDD (2nd Dec.)	0.005	0.006	0.005	0.006	0.006	0.005	0.006
	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Tenant x CDD (1st Dec.)	-0.011	-0.007	-0.008	-0.007	-0.008	-0.008	-0.008
	(0.011)	(0.012)	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)
Account Fixed Effects	YES	NO	NO	NO	NO	NO	NO
Time F.E.s, Acct. Trend	YES	YES	YES	YES	YES	YES	YES
Switchers Controls	YES	YES	YES	YES	YES	YES	YES
Characteristics Controls	YES	YES	YES	YES	YES	YES	YES
Observations	40,962	40,962	40,962	40,962	40,962	40,962	40,962
Accounts	1,126	1,126	1,126	1,126	1,126	1,126	1,126
R-squared (within)	0.095	0.071	0.072	0.072	0.072	0.072	0.072

Notes: The dependent variable in columns (1-5) is the natural log of electricity use in a billing month. Column (1) augments the specification estimated in column (5) of Table 3 to include a building stories quartile dummies interacted with cooling and heating degree days. Columns (2)-(7) present specifications without firm fixed effects. Column (2) includes building type and NAICS code dummy variables, year of construction, number of stories and building size in square feet. Column (3) replaces the number of stories with dummy variables for each story. Column (4) includes quartile dummies for year of construction, number of stories, and building size. Columns (5)-(7) includes the same variables in the form of tercile, quintile and sextile dummies, respectively. Additional controls included in all regressions are cooling degree days, heating degree days, and heating degree days interacted with contract type.