Quantifying the impact of green leasing on energy use in a retail portfolio: limits to big data analytics

Ramon Granell & David C. H. Wallom (Corresponding Author)
Oxford e-Research Centre, University of Oxford
7 Keble Road
Oxford, OX1 3QG
UK
ramon.granell@oerc.ox.ac.uk
david.wallom@oerc.ox.ac.uk

Kathryn B. Janda & Julia Patrick
Environmental Change Institute, University of Oxford
South Park Road
Oxford, OX1 3QY
UK
katy.janda@ouce.ox.ac.uk
julia.patrick@ouce.ox.ac.uk

Susan Bright
New College, University of Oxford
Holywell St
Oxford, OX1 3BN
UK
susan.bright@new.ox.ac.uk

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Abstract

The retail sector is a significant contributor to any industrialised economy and, as a result, a major consumer of energy. Large retailers are aware of the contribution energy makes to their operational costs and of many opportunities available for efficiency measures. However, many retailers are tenants rather than owner-occupiers greatly complicating the implementation of energy and carbon saving technologies ('energy upgrades') because of this predominance of leasehold properties. This introduces a barrier as many of the larger, and hence more impactful, energy efficiency measures require active collaboration between the (landlord) owner and (tenant) occupier for successful implementation, possibly requiring changes to either the building fabric or plant/equipment.

New mechanisms have been developed aiming to smooth this possible barrier, through the use of environmentally conscious legal instruments: either Memorandum of Understanding (MoU) between parties with existing tenancy agreements; or directly inserted clauses specifying mechanisms for collaboration between parties within new lease agreements, so called 'Green Leases' (GL). This paper aims to explore whether there are quantifiable benefits from their use.

Using data from a large UK retail chain we have investigated, using a number of different analytical methods, the visibility of consumption changes after the introduction of an MoU or GL for a number of different classes of stores operated. With the limited dataset available it is, however, difficult to establish a clear causal link between their introduction and statistically significant consumption changes. As such we discuss these limitations and how with the addition of further sources of information we may be able to improve on the analyses performed.

Introduction

Improving the energy efficiency performance of existing building stock is considered a key component of – and opportunity for – meeting the UK's carbon reduction targets (DECC, 2014). In fact, buildings in the commercial sector are estimated to be responsible of 10 % of UK's greenhouse gas emissions overall (WSBF & Carbon Connect 2013).

From an economic perspective, the retail sector in a developed country such as the UK is an essential sector: sales account for 5.7 % of GDP and it employs one in nine working people (ONS 2015). It is also very diverse, supporting a large variety of business models including small independent establishments, high-street chain stores and franchises, shopping centres, hypermarkets and multi-storey department stores. Due to this complexity, management of the energy consumption in this sector provides a challenging but significant opportunity to reduce energy consumption (Janda et al. 2015).

Within the commercial sector, more than half of properties are rented (PIA 2015). In tenanted commercial properties, the tenant-landlord relationship is highlighted as an important barrier for successful implementation of energy efficiency measures (DECC 2014). Leases are a major factor in defining this relationship (Axon et al. 2012). For instance, energy upgrades that require changes to the building fabric or plant/equipment may be prohibited by leases or require collaboration between the landlord as owner of the physical building and the tenant as occupier of the space. Even if a standard lease allows upgrades, sharing their cost can still be contentious. This is known as a "split incentive" where the costs of energy efficiency improvements may be shouldered by the landlord while the benefits (lower energy bills) accrue to the tenant.

The concept of 'green' leasing has been developed to support collaborative approaches to environmental and energy management in rented commercial property (Janda et al. 2016a). It was first implemented by the Australian government as a major occupier of office space (Woodford 2007). In the UK, it has been driven by the Better Buildings Partnership (BBP), which brings together large and institutional commercial property owners and supports sustainability initiatives in the commercial built environment (BBP 2013). The BBP has developed two different routes to the use of green leasing: the use of 'green' clauses within leases (green leases [GL]) and the adoption of 'green' Memorandum of Understanding (MoU). MoUs are (usually) non-binding agreements that can be used alongside existing leases to supplement them without renegotiating the existing contract.

To date, there have been several qualitative analyses of green leases to identify the extent to which green clauses are being used, the types of clauses found, and how this maps against different types of company, property, sector and location, and their role in energy and environmental governance. (Patrick & Bright, 2016; Janda et al, 2016a). Another paper in these proceedings describes recent advances in green leases and leasing in Sweden, Australia, and the UK (Janda et al. 2017). However, there has been no previous attempt to quantify the impact of green leases, in particular one that uses advanced analytic techniques on smart meter data.

In this paper, we perform a quantitative study to explore the impact of GL/MoU introduced as part of a sustainability programme by a major retailer when compared against standard leases (SL). This study has two objectives: (1) to give a quantitative overview of the impact of GL/MoU inside a single retail company, and (2) to understand the limits of a big-data approach using real smart-metering energy data for the property portfolio of a single retailer.

This paper begins with a discussion of the methods used to frame the analysis, which includes a description of the ideal data for our study vs. the available data. We then perform several different analyses of the available data conclude with discussion on the effectiveness of and possible improvements required to the methods chosen.

Methods: Case Conceptions and Conundrums

To perform an ideal analysis of the quantitative impact of green leases, we would need to have (1) perfect information about a stable building portfolio operating under fixed environmental and economic conditions; (2) full access to proprietary legal documents (leases) that would be precision-implemented into employee consciousness (and consciences) at a definite point in time; and (3) faultless gas and electricity data measured in real time for several years before and after the green lease adoption event. In reality, none of these conditions were met in our study, as they are for various reasons either physically or practically impossible to achieve. We were, however, fortunate to work with a very motivated retail partner who provided us with excellent access to their goals and operations, including quantitative data about their building portfolio, internal and external strategy documents, and multiple interviews with the energy management team. This section discusses the information we gathered about our partner's building portfolio, leases, and energy data, as well as assumptions that we made to enable the subsequent analysis.

BUILDING PORTFOLIO

The retailer we worked with is a full-line food and clothing retailer, with approximately 800 stores throughout the UK and another 300 stores in 40 overseas locations. This analysis only pertains to their UK portfolio. Their UK stores are diverse, ranging in size from 183 m^2 to almost 20,036 m^2. Internally, the retailer divides buildings in their portfolio into three different store types that roughly categorize what kind of goods each store sells and whether it is located in town or out of town. We have labelled these categories Type A, B and C in this paper to preserve the retailer's anonymity. Figure 1 shows that these internal classifications have implications for store size and energy use, so we preserve this classification in our analysis. The metadata attached to each building includes floor area, opening hours, and occupancy. Temperature data for the periods covered were obtained from the UK Met Office (MO 2016).

GREEN LEASES AND MOUS

Leases and MoUs are standard legal instruments in commercial property transactions that vary a lot in their detailed application (for example, each lease can specify a different property, lessee, lessor, rental amount, as well as different terms and conditions as negotiated by the tenant and landlord). Green leases or MoUs are made by adding one or more 'green' clauses either directly to the formal lease language – resulting in a "green" lease—or as a formal addendum to the existing lease – resulting in a "green" MoU. Previous studies show that what counts as a "green" lease or MoU can contain a wide variety of ambitions and levels of enforcement, depending on the number and type of clauses they contain (Patrick & Bright 2016; Janda et al 2016a).

Our partner initiated a green lease strategy in their portfolio of properties in 2013 as part of a larger ongoing sustainability program. The green clauses that our retail partner uses for both its MoUs and GLs are based on the BBP green lease toolkit (BBP 2013). We do not have access to the exact green clauses of each individual lease or MoU for confidentiality reasons. However, our partner shared a "library" of green clauses commonly used in their lease and MoU negotiations with landlords. The clauses in operation can be grouped in the following way:

- Green lease and MoU
  - To cooperate on commit to sustainability and provide a forum to discuss sustainability
  - Agree to use reasonable endeavours to agree and comply with an environmental management plan
  - Agreement to share utility data
- MoU only
  - To consider the implementation of specified energy efficiency measures and practices

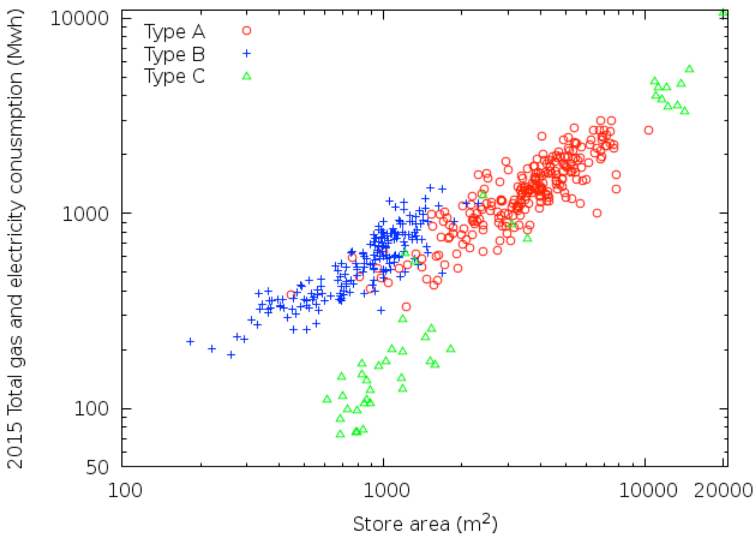

Figure 1. Distribution of energy consumption against store area highlighting the contributions from each different type.

This grouping shows that in this portfolio, MoU terms tend to be more ambitious than GL clauses. Also in this portfolio, MoUs are used more frequently. This could be because MoUs are generally less legally binding, or because they amend an existing lease. For example, it is probably clearer to an existing tenant what energy efficiency upgrades might be made in premises than to a tenant who has yet to occupy the space. At the time of the information gathered for this analysis, our partner had 52 stores with green MoUs and 14 with green leases. The larger number of adopted MoUs means the analysis tends to focus on MoU stores rather than GL stores, which has implications for the both the ambition and enforceability of these tenant/landlord agreements.

The exact date the MoU/GL was signed each store is not easily accessible (even by the retailer without significant additional work) but as a proxy a global adoption date of April 1 2013 has been provided by our retail partner based on when the MoU/GL programme was put into action. We have therefore selected 1/4/2013 as the adoption date for both MoU and GL stores (which we refer to as the 'lease date' below). This lack of precise information with respect to the exact clause formulation for each one of the stores and the precise date of introduction is one of the limits of our study when we quantitatively compare stores.

DATASET

Hourly readings of electricity and gas for UK stores are analysed in this work. Readings are available from January 2009 to December 2015. However not all the stores have readings for all days during this time period, e.g. some of them opened after Jan 2009, other closed before Dec 2015 and there are also some missing values. Pre-processing over the computed daily consumption readings is performed for each store using the following criteria which are applied in series:

1. Stores whose gas readings are constantly zero throughout the period are removed,
2. Electricity daily consumption values that are smaller than 50 kWh and larger than 50,000 kWh based on statistical analysis of the stores are removed,
3. For both electricity and gas readings, a frequency test is performed over remaining non-negative readings, and those stores that have values with the exact value repeated more than 2 % of the total are manually checked. Periods of times with these exact repeated values are found and removed.

Following pre-processing, Table 1 shows the number of stores remaining for each store type and their presence or absence of MoU/GL.

Alongside the consumption data we also have additional metadata available for each store, its floor area and postcode. Only those stores presenting both items of metadata are employed in the analysis to allow further context to be applied to each stores consumption, with floor area used for example for normalisation.

Analysis and results

The quantitative study performed in this paper is based on two different comparisons of the electricity and gas consumption of three groups of stores: stores with green leases (GL stores), stores with MoU (MoU stores) and stores with standard leases (SL stores). Two different aspects of energy consumption will be considered:

1. Time series: Comparing electricity and gas consumption two years before and after the adoption of MoU. This comparison is limited by the need for reasonably consistent time series data over a 4-year period between 2011 and 2015.
2. Portfolio Comparison: Measured consumption of MoU and GL stores is compared to SL stores for 2015, intending to show whether any changes found were transitional only or if there is a longer-term benefit possibly visible in GL- or MoU-stores.

Depending on the data requirements of each analysis, a subset of stores of Table 1 that have readings during the relevant specific time period are selected, these subsets are introduced for each analysis in Tables 2 and 6.

Table 1. Number of stores identified by store type, energy source, and lease.

	Electricity				Gas			
	MoU	GL	SL	Total	MoU	GL	SL	Total
Type A	33	1	215	249	30	1	192	223
Type B	13	13	173	199	8	10	92	110
Type C	5	0	43	48	5	0	38	43
Total	52	14	431	496	43	11	322	376

Table 2. Number of stores used for comparison of consumption before and after the introduction of MoU/GL.

	Electricity			Gas		
	MoU	SL	Total	MoU	SL	Total
Type A	32	202	234	29	180	209
Type B	11	152	163	5	72	77
Total	43	354	397	34	252	286

MOU TIME SERIES ANALYSIS

In this section, we perform a time series analysis to investigate potential changes in energy consumption (both electricity and gas) before and after MoU were adopted, a date which we have estimated to be 1 April 2013, as described above. This analysis covers only MoU stores because GL could not effectively be assessed in a time series due to the lack of "before" data.

This analysis uses two forms of baseline to investigate the energy consumption of MoU stores before and after the adoption date. Firstly, it self compares each MoU stores evolution of consumption, and then second, each MoU store is compared to the wider group of SL stores. The analysis is performed each time over electricity, gas (if existing for that property) and total consumption. Each of these are performed over both temperature normalised and non-normalised consumption data. The total consumption is calculated by adding the electricity and gas consumption as both datasets are supplied in kwh.

Time Series: Self Comparison

The first comparison performed is to compute average daily consumption of both electricity and gas per store from Monday to Saturday (chosen as they have near identical trading times), before the lease date (CBL) and after the lease date (CAL). It is important that the periods of time before and after the lease date are of similar duration and cover the same months to reduce seasonal variability. Therefore, for electricity, we take the smaller of the maximum number of whole years that the store has readings before and after 1/4/2013 when the year has more than 90 % valid readings, *i.e.,* if we have a store with data from 1/1/2009 to 31/12/2015, we will use readings from 1/4/2011 to 31/3/2013 to compute CBL and reading from 1/4/2013 to 31/3/2015 to compute CAL. For gas, we searched for stores that have valid electricity values and contain more than 10 % of gas readings with positive values per year. The last constraint is that the years used for electricity and gas analysis should be the same, if the store has valid gas readings. Within the analysis we will use only subsets that contain five or more stores with valid readings. Overall we remove 100 stores in total (9 MoU, 14 GL & 77 SL) from the dataset through these enhanced constraints. Therefore, we consider only the MoU stores, of which there are 32 Type A stores, 11 Type B stores and, 0 Type C with electricity data and 29 Type A stores, 5 Type B stores and, 0 Type C with accompanying gas data as shown in Table 2 classified by store and lease type.

As an example, Figure 2 shows the electricity consumption of each Type B MoU store before and after the lease date, ordered by their average daily consumption. All the error bars in this document have the mean in the centre and the extremes are the mean plus/minus the standard deviation. Although the means of the CAL (μ_{CAL}) are smaller than their respective means of CBL (μ_{CBL}) for most of the stores (72.4 % of stores have μ_{CAL} smaller than μ_{CBL}), there is considerable overlap of the error bars in the two consumptions. Though a decrease in the consumption of most stores after the lease date is visible, the variability of the daily consumption given by the standard deviations are high and overlapping, therefore statistical differences between them cannot be established.

For each store, the percentage change of the mean consumption can be computed:

$$\Delta_\mu = \frac{\mu_{CAL}-\mu_{CBL}}{\mu_{CBL}} \cdot 100$$

For instance, store #10 in Figure 2 has μ_{CBL} = 2,552.7 kWh and μ_{CAL} = 2,370.3 and therefore Δ_μ = -7.14 %, *i.e.*, there has been a decrease of 7.14 % in electricity consumption after the lease date. The change in store electricity and gas consumption after the lease date and the mean and standard deviation of Δ_μ for all the stores with MoU of both types A and B are shown in Table 3.

Time Series: Comparison between MoU and SL stores

The same analysis as performed in the self-comparison for MoU stores has been performed over the SL stores obtaining a similar percentage of stores (81.7 %) that decrease their consumption after the lease date.

For Type A stores, the mean Δ_μ of electricity computed separately over the stores for MoU and SL stores is the same, -6.5 %. However, the standard deviation differs, being greater for the Δ_μ over stores with MoU than without. This is an indicator of higher variability for the Δ_μ of the MoU stores. In fact, if we consider just the stores that decrease their electricity consumption the average of Δ_μ is -9.4 % and -8.6 % for MoU and SL stores, respectively, *i.e.*, the stores with MoU that decrease their consumption have almost 1 % more improvement on average than stores without MoU which also decrease their consumption.

When considering gas consumption, 62.1 % Type A stores decrease their mean daily consumption after the lease date. In this case the variability of the gas is higher than for electricity. This may be because gas is used dominantly for space heating and is therefore influenced by seasonal variability. The mean Δ_μ of gas consumption all the Type A MoU stores is +6.0 %, *i.e.*, there is an average increase of 6.0 % of gas consumption considering all MoU stores. However, the standard deviation is also high indicating that there is a high level of variability in Δ_μ among these stores. Now we compare these with SL stores. These stores have a slightly smaller percentage that decrease their daily CAL, at 60.0 %, but on average across the whole portfolio decrease their consumption 4.1 % after the lease date. The standard deviation of Δ_μ is greater for MoU stores than for SL stores, indicating the greater level of variability of Δ_μ for MoU stores when compared to SL stores.

For Type B stores, a similar percentage of MoU (-2 %) and SL (-4.1 %) stores decrease electricity consumption after the lease date, (see Table 3 row 2). For gas, the percentage of stores with MoU that decrease the CAL is 100 % (5 of 5), meanwhile, just 54.2 % of SL stores decrease CAL. The mean Δ_μ is very different for both groups: -17.7 % for MoU stores and +130.9 % for SL stores. This huge increase in the consumption for the SL stores is due to the relative difference of CAL and CBL for many stores. This can be due to a number of different reasons such as significant use of heating due to colder temperatures for the years on average after the lease date or physical changes to the buildings' main heating systems.

Table 4 compares the aggregate total energy consumed before and after the lease date between MoU and SL stores. The percentage of stores that decrease their consumption after the lease date is greater for the Type A SL stores than MoU stores. The opposite happens with Type B stores. For the Type A stores, the values of the means of Δ_μ of the stores with MoU are higher (less of a reduction in energy consumed) in general than values of SL stores. For Type B stores this is again reversed, i.e. the means of Δ_μ computed over MoU stores are in general equal or lower than values for SL stores.

The variation of gas consumption has a large dependency on external temperature (due to the dominance of space heating as the major consumer). The magnitude of this consumption is far greater than other uses of gas (e.g. water heating)

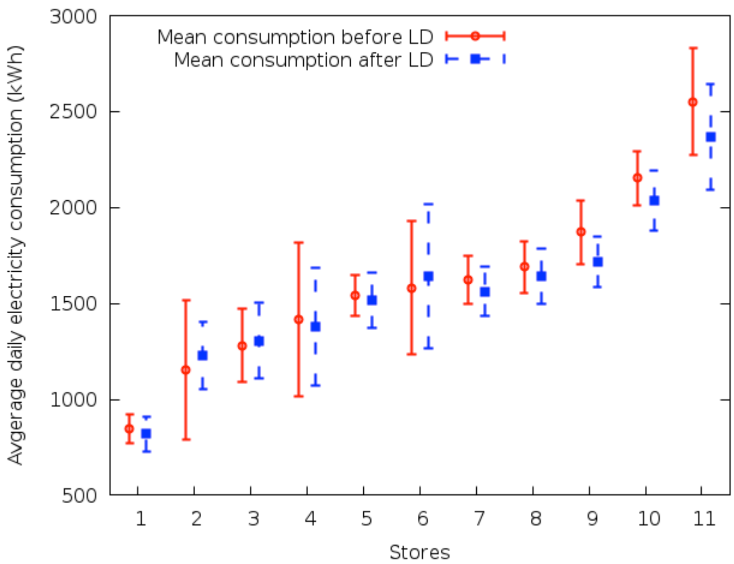

Figure 2. Comparison of daily electricity consumption before and after the lease date for each Type B stores with MoU.

Table 3. Comparing CBL and CAL showing the percentage of stores that decrease consumption after the lease date ($\mu_{CAL} < \mu_{CBL}$) including the mean and standard deviation.

	Electricity				Gas			
	% of Stores with a reduction in consumption		Stats. Ratio (Mean Δ_μ, Std Deviation in Δ_μ)		% of Stores with a reduction in consumption		Stats. Ratio (Mean Δ_μ, Std Deviation in Δ_μ)	
	MoU	SL	MoU	SL	MoU	SL	MoU	SL
Type A	78.1	81.7	(-6.5, 9.2)	(-6.5, 6.5)	62.1	60.0	(6.0, 65.6)	(-4.1, 37.0)
Type B	72.7	72.4	(-2.0, 4.5)	(-4.1, 7.2)	100.0	54.2	(-17.7,13.7)	(130.9, 599.7)

Table 4. Results for total energy. %Dec is the percentage of stores that decrease consumption after the lease date and Δ_μ, Δ_μ-Dec and Δ_μ-Inc includes the mean and standard deviation of Δ_μ for all stores, only stores that decrease consumption and only stores that increase consumption, respectively.

	MoU				SL			
	%Dec	Δ_μ	Δ_μ-Dec	Δ_μ-Inc	%Dec	Δ_μ	Δ_μ-Dec	Δ_μ-Inc
Type A	68.8	(-4.2, 12.4)	(-10.1, 6.3)	(8.9, 23.0)	76.7	(-6.6, 8.8)	(-10.0, 6.6)	(4.7, 18.4)
Type B	72.7	(-3.5, 5.3)	(-6.4, 2.0)	(4.2, 11.9)	69.1	(-3.4, 9.0)	(-7.8, 5.8)	(6.5, 16.4)

Table 5. Comparing CBL and CAL showing the percentage of stores that decrease temperature normalised consumption after the lease date ($\mu_{CAL}<\mu_{CBL}$) including the mean and standard deviation.

	Gas				Total energy			
	% Store decrease		Stats. Ratio (Mean, Std deviation)		% Store decrease.		Stats. Ratio (Mean, Std deviation)	
	MoU	SL	MoU	SL	MoU	SL	MoU	SL
Type A	51.7	45.6	(1.2, 0.7)	(1.0, 0.4)	50.0	54.5	(1.0, 0.1)	(1.0, 0.1)
Type B	60.0	45.8	(0.9, 0.2)	(2.5, 6.3)	36.4	38.2	(1.1, 0.1)	(1.0, 0.1)

which we would consider season independent and therefore a constant baseline and small in comparison. We therefore normalise consumption considering external temperature where previously we were investigating the differences in total consumption. For each store this is obtained using the data from its closest meteorological station. We computed separately for each store the aggregated daily consumption for the period before/after the lease date and divided this by the total number of heating degree days (HDD) (Day 2006) with a base temperature 15.5 °C during the specific time period. For instance, for one particular Type A MoU store the aggregated CBL is 2121.8 MWh that was consumed during 587 days before the lease date and the total number of HDD during this period is 2944.3, producing an average consumption of 720.63 kWh/HDD. For the same store, the aggregated CAL is 2441.9 MWh consumed during 566 days after the lease date and the total number of HDD during this period is 2715.4, producing an average consumption of 899.30 kWh/HDD. We compute a ratio to see the evolution of the temperature-normalised consumption. For the previous example 899.30/720.63=1.25, meaning that there is a 25 % of increase of consumption after the lease of temperature-normalised consumption. A ratio greater than one indicates that store consumption has increased after the lease date and vice-versa.

For Type A MoU stores, 51.7 % decrease their consumption, 6.1 % more than SL stores (Table 5). However, the averaged ratio CAL/CBL is higher for MoU stores than for SL stores due to a number of MoU stores with high ratios.

For Type B stores using the temperature-normalised gas consumption, we see a decrease in consumption for four of five MoU stores (80 %), and correspondingly only 45.8 % for SL stores (see Table 5). The ratio for MoU stores has an average of 0.9 and a small standard deviation (0.2), while SL stores have a larger mean and standard deviation, 2.5 and 6.3, respectively. This smaller standard deviation for MoU stores implies that these stores decrease gas consumption more consistently after April 1 2013 than SL stores. It is important to note the difference in size between the two groups as there are five MoU and 72 SL stores (see Table 2).

For store type (A & B), the percentages of both MoU and SL stores that decrease their total energy consumption are very similar. Here we also normalise the electricity data according to temperature using the same method as described previously to capture cases where there is a single energy type supplied to cover all usage including space heating. The average of the ratios are all close to one, *i.e.* the temperature-normalised energy CAL and CBL is similar considering all the stores together.

PORTFOLIO COMPARISON OF ENERGY CONSUMPTION AMONG STORES FOR 2015

In this section, we compare the energy consumption of stores using data from 2015 only. We select this year as it is the most recent year for which we have the most complete data. For electricity, we select those stores (485) that have 90 % of daily readings for 2015 (*i.e.,* have more than 328 days with valid data). For gas, we select from those stores that fulfilled the previous electricity criterion and additionally apply another criteria of stores that have 20 % of daily readings greater than 0 for 2015 (*i.e.,* more than 71 days with positive values) (345). After applying these criteria, we use only store types that have at least five valid stores. Table 6 shows the number of stores used in this analysis per group.

As we are now directly comparing the actual consumption values between different stores we must account for their differing physical size. Therefore, we normalise consumption by floor area. Figure 3 shows the average and standard error of average daily electricity consumption of the premises grouped by store type and lease type. In this case, we observe that the means of Type B stores with MoU and GL are lower than for SL stores. However, the standard deviation overlaps between both groups indicating that there is not any statistical difference. For the Type A and C stores, the reverse is seen, the average for MoU stores is greater than SL stores. Again, the error bars overlap each other.

We again normalise for temperature as previously discussed for both types of energy source to compare the stores independent of location and season. Figure 4 shows the average of the aggregated temperature-normalised energy consumption by floor area over the stores grouped by lease and store type. MoU stores have an average slightly over that for SL stores for all three type of stores. For the Type B stores, stores with GL have greater average than SL stores. Again, there is a high degree of overlap over all the error bars. We need also to be aware of the small size of some of the store groups that we are using in the analysis with Type C stores.

Another way to visualise the consumption by area of the MoU/GL stores with respect to the overall portfolio is with the box-and-whisker plot. Figure 7 shows the minimum, maximum, first and third quartile and median of the average daily consumption of the stores grouped by store type. We have highlighted MouU/GL stores to understand where they are located with respect to overall consumption. The quarter interval that includes the highest consumption values (the top one in the charts) has the widest range for the three store types. It indicates that there are some stores that have anomalously high values compared to most stores of the same type. Table 7 contains the number and percentage of stores in each one of the quarter intervals of the box-and-whisker charts for the stores with MoU. For the Type A MoU stores, 45.5 % of the stores whose consumption by area value are below the median, meanwhile for Type B stores there are 53.9 % above the median. In both cases, the differences of the percentage of stores below and above the median are not significant. Most of the Type C stores with MoU (four of five) are in the highest quartile.

Electricity daily profile

The average daily electricity profile of all the stores with readings during 2015 is also computed (gas profile is not computed due to seasonality). These daily profiles are normalised by floor area and grouped by lease and store type. Figure 6 and Figure 7 show these profiles for the Type A and B stores, respectively. For the Type A stores, the profile computed with SL stores has lower consumption than the profile computed with MoU stores. The opposite fact happens for the Type B stores, where the profile of MoU stores has lower consumption than the profile SL stores. Type A stores with GL has lowest consumption during the peak period but highest consumption during off-peak period. These results are consistent with the values obtained when we compute the daily mean values (see Figure 3).

Discussion & Conclusions

In this work, we have compared the electricity and gas consumption of stores with GL/MoU before and after the date the green clauses were (deemed) adopted, as well as comparing the consumption of stores with and without MoU/GL for a full year.

Table 6. Number of stores by energy source and lease types for the comparison of consumption for 2015.

	Electricity				Gas			
	MoU	GL	SL	Total	MoU	GL	SL	Total
Type A	33	–	208	242	28	–	180	208
Type B	13	11	172	196	8	9	82	99
Type C	5	–	42	47	5	–	33	38
Total	51	11	422	485	41	9	295	345

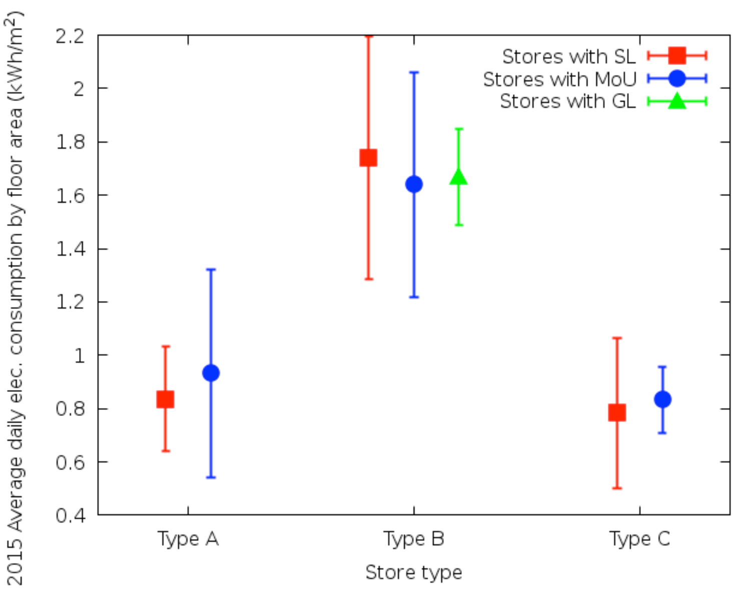

Figure 3. Mean and standard dev. of the daily electricity consumption by store area separated by lease and store type.

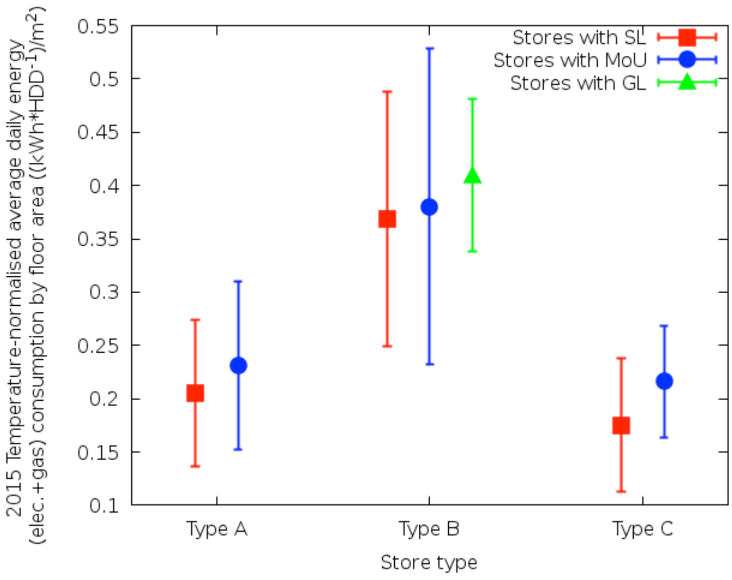

Figure 4. Mean and standard dev. of the aggregated temperature-normalised energy consumption by store area separated by lease and store type.

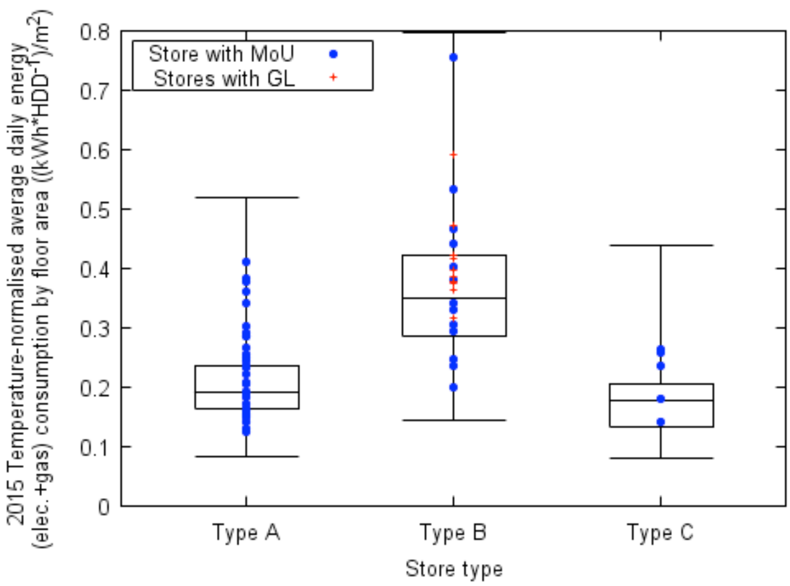

Figure 5. Box plot of the aggregated temperature-normalised energy consumption by floorarea of all the stores separated by store type and exact values of the stores with MoU/GL.

Table 7 Distribution of MoU stores per quarter intervals considering aggregated temperature & area normalised energy consumption (kwh-HDD/m²) (see Figure 5).

Store type/Interval	[0 %,25 %]	[25 %,50 %]	[50 %,75 %]	[75 %,100 %]
Type A	27.3 % (9)	18.2 % (6)	15.2 %(5)	39.4 % (13)
Type B	23.1 % (3)	30.8 % (4)	15.4 % (2)	30.8 % (4)
Type C	0 % (0)	20.0 % (1)	20.0 % (1)	60.0 % (3)

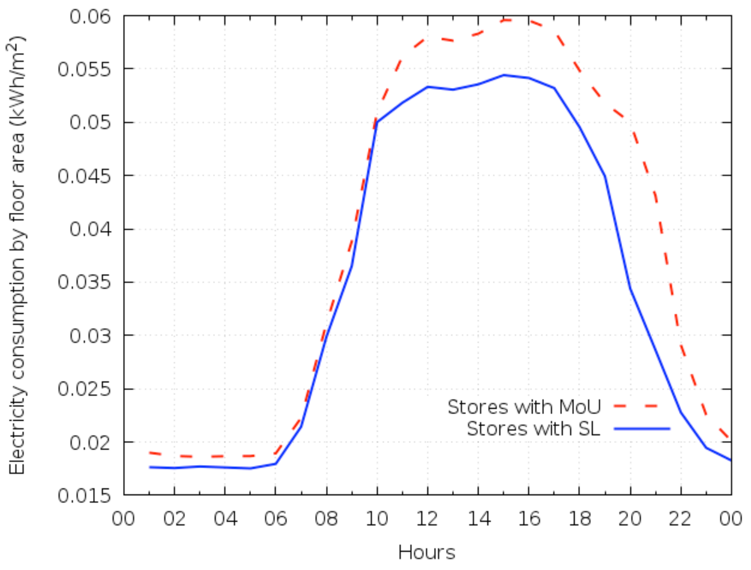

Figure 6. Electricity profiles computed with readings during 2015 of Type A stores.

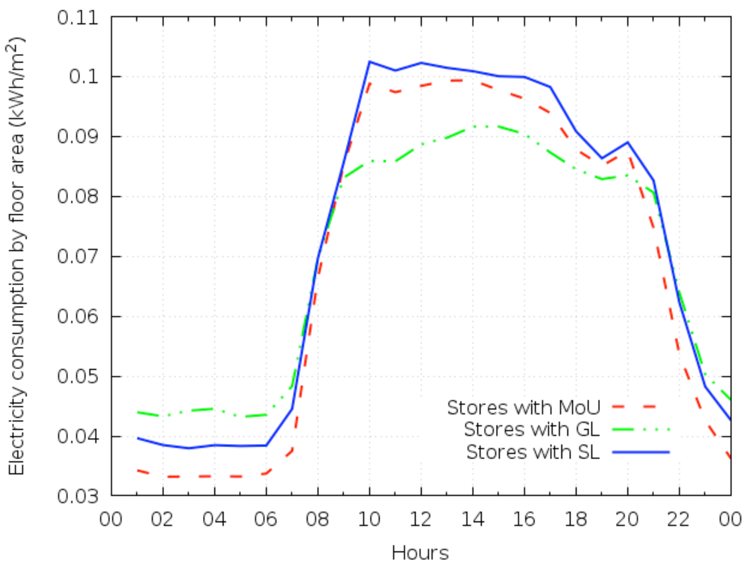

Figure 7. Electricity profiles computed with readings during 2015 of Type B stores.

For electricity consumed during the periods before and after the date of lease introduction, MoU stores on average do decrease their consumption in the period afterwards. However, the percentage of MoU stores that do so is similar to that for SL stores. Therefore, to make a definitive causal link between the decrease and the MoU/GL introduction we would have to remove the advantages gained from energy efficiency measures that are enacted across all the portfolio, i.e. that would have happened anyway. In addition, the average variability of the stores during the two periods is similar for both stores with and without MoU.

For temperature-normalised gas consumption, the number of stores decreasing consumption after the lease date for Type A stores is again similar to the comparable SL stores, but, the percentage of Type B MoU stores that decrease their consumption is significantly higher than the percentage of Type B SL stores (the average of CAL/CBL is also significantly lower in this case).

Comparing the energy consumption of stores for 2015, we see that the averages of both groups (MoU and SL stores) are quite similar (i.e. the error bars of each group overlaps each other). Type B MoU/GL stores have smaller electricity consumption that Type B SL stores, though the opposite occurred with Type A stores where the consumption of the MoU stores is slightly higher than SL stores. When we compare the aggregated energy consumption, differences between stores with and without MoU are not significant. The exact cause of this store type wide change would need to be investigated directly with a number of these stores to ensure that we have better visibility of how MoU or GL sanctioned changes fit with the overall energy efficiency activities across the portfolio.

Overall therefore from this analysis, we cannot categorically claim that stores with MoU/GL have less or more energy/electricity/gas consumption that stores without MoU/GL (*i.e.* we cannot see that the differences between the groups are statistically significant). However, there are interesting tendencies that suggest that those Type B stores with MoU have lower consumption than those Type B stores without MoU/GL when considering their electricity consumption and that Type B stores show a reduction in gas consumption following introduction.

This paper describes one of the first attempts at using analytics to investigate the effect of the introduction of green clauses in property arrangements over real data of a significant portfolio of establishments of the same organisation. We have also described the limitations, mostly around the lack of availability of different and corroborating information about;

- specific details about content of individual legal agreements describing landlord tenant relationships and obligations,
- the dates of entry and extent to which legal agreements were therefore relevant to day to day energy practices,
- property use, including exact utilisation of different areas of ground space within the building which have different energy density and environmental conditions requirements,
- physical building information such as year of construction, materials, structure, orientation, environment.
- Significant sub metering information that may be more easily linked directly to drivers of energy usage and different energy efficiency measures taken on an individual premesis level.

This information, if available at all, is normally only accessible by different parts of the company and requires a non-trivial number of resources to coordinate and analyse (Janda et al. 2016b). Therefore, to make it available for analytics in any meaningful manner would require its storage and access to be available through some form of machine readable service and if possible following a well-defined schema to allow comparisons quickly and easily between different parts of the property portfolio.

This early analytic study does not prove that GL/MoUs lead to quantifiable impacts on energy consumption. Changes in consumption appear to occur across the whole portfolio which may be a reflection of the retailers' energy management policies. Not being able to observe clear energy differences between SL and GL/MoU stores does not, however, mean that these instruments do not have an effect on energy management methods and practices and hence consumption. Reasons include;

- some clauses are designed to achieve specific objects, for example, sharing data may help achieve compliance requirements,
- the effects can be slow and the analysed periods are quite short. It would, for example, be more useful to repeat the analysis over longer time periods before and after establishment of the clauses such as five or ten years.
- we need to compare stores that are more similar above and beyond just their type (A, B or C). This can include detailed internal differences, building differences and effectiveness of local regime/management inputs.

Overall, green clauses within leases should be seen as tools to help to induce social, behavioural and physical changes in energy consumption. These changes however, should be translated into tangible energy reductions or peak shifts but which may be only directly discernible among smaller groups of stores where there are both external and internal similarities for comparison.

References

Axon, C. J., S. Bright, T. Dixon, K. B. Janda, & M. Kolokotroni. 2012. "Building communities: reducing energy use in tenanted commercial property." *Building Research & Information* 40 (4): 461–472. DOI: 10.1080/09613218.2012.680701.

BBP 2013. Better Buildings Partnership. "BBP Green Lease Toolkit". http://www.betterbuildingspartnership.co.uk/download/bbp-gltk-2013.pdf

BPF 2016. British Property Federation. Model Commercial Lease. http://modelcommerciallease.co.uk/leases/

Collins et al. 2016. Collins, D., Junghans, A., & Haugen, T. "Green Leasing in Theory and Practice: A Study Focusing on the Drivers and Barriers for Owners and Tenants of Commercial Offices". In Proceedings of the CIB World Building Congress 2016 Creating Built Environments of New Opportunities, June 2016, Tampere Finland) Vol 1, pp 419–431. https://tutcris.tut.fi/portal/files/6186667/WBC16_Vol_1.pdf

Day T. 2006. "Degree-days: Theory and Application". The Chartered Institution of Building Services Engineers, UK. http://www.degreedaysforfree.co.uk/pdf/TM41.pdf

DECC 2014. Department of Energy and Climate Change. "Private Rented Sector Minimum Energy Efficiency Standard Regulations (Non-Domestic) (England and Wales) – Consultation on Implementation of the Energy Act 2011 Provision for Energy Efficiency Regulation of the non-Domestic Private Rented Sector". https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/401378/Non_Dom_PRS_Energy_Efficiency_Regulations_-_Gov_Response__FINAL_1_1__04_02_15_.pdf

Hinnells et al. 2008. Hinnells M., Brigth S., Langley A., Woodford. L. & Schiellerup T. B "The greening of commercial leases", Journal of Property Investment & Finance, Vol. 26 Iss: 6, pp 541–551. http://dx.doi.org/10.1108/14635780810908389

Janda, et al., 2015. Janda, K. B., J. Patrick, R. Granell, S. Bright, D. Wallom, & R. Layberry. 2015. "A WICKED Approach to Retail Sector Energy Management" In Proceedings of eceee Summer Study, June 2015 (Presqu'île de Giens, France). Vol. 1 – Foundations of Future Energy Policy, pp. 185–195. http://www.energy.ox.ac.uk/wordpress/wp-content/uploads/2014/07/2015.06-Janda-Patrick-et-al-ECEEE.pdf

Janda et al., 2016a. Janda, K. B., Bright, S., Patrick, J., Wilkinson, S., & Dixon, T. J. "The Evolution of Green Leases:

Towards Inter-organizational Environmental Governance" Building Research & Information. Vol 44, pp. 660-674. http://dx.doi.org/10.1080/09613218.2016.1142811

Janda et al., 2016b, Janda, K. B., D. Wallom, R. Granell, & R. Layberry. 2016b. "Shopping for Success: Numbers, Knowledge, Time & Energy." In *Proceedings of ACEEE Summer Study on Energy Efficiency in Buildings*, August 21–16, 2016 (Asilomar, CA). Vol. 8, pp. 8.1–8.12. American Council for an Energy Efficient Economy: Washington, DC. http://aceee.org/files/proceedings/2016/data/papers/8_627.pdf

Janda et al., 2017. Janda, K. B., S. Rotmann, M. Bulut, & S. Lenannder. 2017. "Advances in green leases and green leasing: Evidence from Sweden, Australia, and the UK." In *Proceedings of eceee Summer Study*, 29 May–3 June 2017 (Toulon/Hyères, France). Vol. 2 – Policy governance, design, implementation and evaluation challenges. European Council for an Energy Efficient Economy: Stockholm, Sweden. http://www.eceee.org/library/conference_proceedings/eceee_Summer_Studies

MO 2016. UK Meteorological Office "MIDAS Land Surface Station data (1853-2016)". http://badc.nerc.ac.uk/view/badc.nerc.ac.uk__ATOM__dataent_ukmo-midas

ONS 2015. Office for National Statistics. "Retail Sales: September 2015, United Kingdom". http://www.ons.gov.uk/businessindustryandtrade/retailindustry/bulletins/retailsales/2015-10-22

Patrick & Bright, 2016. J Patrick and S J Bright, 'WICKED insights into the role of green leases' (2016) Conveyancer 264.

PIA 2015. Property Industry Alliance (PIA) (2015), "Property Data Report 2015". http://www.ipf.org.uk/resourceLibrary/pia-property-data-report-2015.html)

Woodford, L. 2007. "The Green Lease Schedule", In Proceedings of eceee Summer Study, June 2007 (Colle Sur Loop, France), pp. 547–556. http://www.eceee.org/library/conference_proceedings/eceee_Summer_Studies/2007/Panel_3/3.343/paper

WSBF & Carbon Connect 2013. Westminster Sustainable Business Forum and Carbon Connect. "Building Efficiency: Reducing Energy Demand in the Commercial Sector: London". http://www.policyconnect.org.uk/wsbf/sites/site_wsbf/files/report/403/fieldreportdownload/wsbfreport-buildingefficiencypdf.pdf

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