Effects of Construction Activities on Residential Electricity Consumption: Evidence from Singapore's Public Housing Estates

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Abstract:

This study aims to empirically test the effects of negative environmental externalities (i.e. noise pollution) due to construction activities within half to one kilometer (km) radius and how households react to such externalities by increasing the use of air-conditioners to mitigate noise from the construction work. We use a unique dataset of electricity consumption by public housing residents in Singapore measured at the building level and merge it with the dataset of construction sites for the periods from 2009 to 2011. Using a difference-in-differences approach, we find that electricity consumption by the households living close to the construction sites increases by 6% compared to the households who are not affected by noises from construction sites during the construction periods, after controlling for building and month of the year fixed effects. The results remain robust after controlling for spatial autocorrelated lag and error terms. The economic cost of the construction externalities for each household amounts to approximately S$98 per annum. We also find that the increases in electricity consumption of the affected households were persistent, and the electricity consumption of the affected households did not revert to the pre-construction levels, after the removal of the negative externality.

Keywords: *Electricity Consumption, Negative Externalities, Construction Activities, Public Housing, Demand for Comfort*

JEL Code: D10, Q40, R10

1. Introduction

Rising energy consumption is a global concern. Household electricity consumption is growing at an alarming pace in tandem with rapid urbanization processes, especially in emerging economies. Energy (electricity) consumption is one of the key factor inputs in the "production" of dwelling comfort (indoor air temperature) for households (Quigley, 1984; Quigley and Rubinfeld, 1989). Households use energy (electricity) ("purchased comfort") to substitute deficiencies caused by poor housing designs (such as rooms, vintage, etc.) and undesirable climatic conditions to attain expected interior comfort of dwelling ("produced comfort"). Households increase electricity consumption to mitigate effects of exogenous shocks that could reduce their expected comfort level, such as noise and dust from nearby construction sites.

When facing construction noise and pollution (externalities), households either adopt a passive approach by adjusting their lifestyle while hoping that the noise could be kept within an acceptable level via government regulations[1]; or take a pro-active action to mitigate the externalities. Many affected households may "*self-protect*" against construction noise by shutting off windows and doors and air-conditioning indoor environment. As there is no contractual relationships between contractors/builders and households affected by construction noise, it is difficult to verify if the "self-protection" actions of households could induce moral hazard in contractors/builders (Ehrlich and Becker, 1972).[2] While it is not within the scope of this study to test the moral hazard behavior of contractors/builders, this study instead aims to empirically test how electricity consumption behavior of households could be influenced by the self-initiated protection in mitigating local externalities associated with noise and dust from adjacent construction sites.

Traditionally, there are two approaches by which negative environmental externalities are valued. The first approach uses stated preference methods (e.g., contingent valuation) to

[1] In Singapore, the government enacts the "Environmental Protection and Management (Control of Noise at Construction Sites) Regulations" (Chapter 94A Section 77) to protect excess noise/dust generated from construction sites. Under the act, builders of residential projects are required to abide by the maximum permissible noise level of 75 decibels (an equivalent continuous noise level over a period of 12 hours between 7am-7pm).

[2] Ehrlich and Becker (1972) develop a theoretical framework to explain moral hazard in the demand for insurance. In their insurance demand model, self-insurance and self-protection are considered as alternative systems to market insurance. While self-insurance is intended to minimize the size of a loss, self-protection is meant to reduce the probability of a loss. They show that market insurance leads to the moral hazard behaviour of insurers.

estimate subjective social costs associated with environmental disturbances. The second approach uses market transaction data to objectively estimate costs of negative externalities. Our quasi-experiment uses Singapore's electricity consumption data at the building block level to test behavioral responses of households to negative externalities caused by construction activities on adjacent sites. The advantages of using Singapore's electricity consumption data are two-fold. First, Singapore being located in the tropical climate zone has a relatively constant temperature with high humidity. Typical households use on average 30% of electricity in air-conditioners to provide cooling comfort for internal space.[3] Second, Singapore is a densely-built urbanized city, where new construction activities are a common part of the urban fabric. Construction noise could induce "*self-protection*" responses of households to minimize dis-utilities in dwelling by using air-conditioners to cool indoor space. Therefore, externalities caused by nearby construction activities could significantly increase electricity costs (externality costs) incurred by households.

As "comfort" level is not observable in reality, this study uses a distance measure to proxy the intensity of construction noise externalities in our identification strategy. We use two distance dummies to identify housing estates that are located within 0.5 kilometer (km) and 1.0 km (by shortest distance) from construction sites, respectively, depending on the scales of construction projects (by square meters gross floor areas) as proxies for the effects of environmental externalities (construction noise). By the distance to the nearby construction sites, we sort the sample buildings into a treatment group consisting of building blocks located within 0.5 km of construction sites with total gross floor areas (gfa) of less 5000 square meters (sqm), and/or 1.0 km of large construction sites with more than 5000 sqm in gfa. Other buildings that are located outside the "treatment" boundary are sorted into a control group. The construction sites data are obtained from the Building Construction Authority (BCA). We then empirically test for variations in block-level electricity bills for the two groups before and during the construction period.

Using a set of electricity bill data for public housing blocks in Singapore for the periods from 2009 to 2011, our results show that the "treatment" housing blocks consume significantly more

3 An energy report published by the Energy Efficient Program Office (E^2PO), a Singapore's government agency led by the National Environment Agency (NEA) showed that the household sector consumes one-fifth of the total electricity in Singapore, and 30% of the household electricity was accounted for in the use of air-conditioners.

electricity in the same months after controlling for heterogeneity in housing attributes and location fixed effects. The negative externality caused by construction noise is estimated at about 6.0%, based on differences in electricity consumption between the treatment samples and the control samples. In term of average monthly electricity consumption, the 6% differences is translated into an equivalent of 30.15 kWh per household[4]; and compared with the monthly electricity consumption of 184 kWh, 273 kWh and 373 kWh for 2-room, 3-room and 4-room public housing flats,[5] respectively, the construction noise externalities cause electricity consumption to increase by between 8.1% and 16.4% per households. If the electricity tariff of 0.27 cents as in 2009 is used as the reference, the construction noise externalities are translated into approximately S$9,770 per block per annum in the economic term.[6] In our total sample of 4682 housing blocks, 1617 blocks were identified as the treatment blocks; and the total economic costs are estimated at around S$15 million in an aggregate term for households living in these blocks.

The results imply that households use self-protection measures, such as air-conditioning indoor environment to mitigate externalities associated with construction noise and pollution from nearby construction sites. This action causes the electricity bills of housing units in treatment blocks to increase relative to other far-away blocks, *ceteris paribus*. We find that household electricity consumption behaviors did not revert to the original pattern, after construction activities have been completed. Increases in electricity consumption are persistent; and we find no evidence of rebound effects as in Reiss and White (2005). The habit persistence behavior of household is one possible reason for not observing the rebound effects (persistence in electricity consumption behavior) in the treatment households, who may find it hard to switch back to non-air-conditioned indoor environment after the construction works have been completed.

This paper makes three contributions to the literature on residential energy consumption. First, we find evidence to suggest that households shut off windows and doors, and air-condition

[4] We do not have household level data to directly compute externality costs for each household. We make an assumption that a typical public housing (HDB) block consists of approximately 100 housing units. The numbers of households may differ by block layout size, and number of floor in each block.

[5] The electricity consumption data are based on the statistics reported as in December 2014by Singapore Power Limited, the main utility firm that distributes electricity in Singapore.

[6] Based on the 100 households per block assumption, the per household cost of externality works out to be approximately S$ 97 for a household living near a construction site and subject to noise and dust from the site for a period of 1 year.

their rooms as a “self-protection” mechanism to negate “dis-utilities” caused by construction externalities. These households are unlikely to endure passively with diminishing levels of dwelling comfort caused by construction noise. Second, we estimate the economic impact of negative externalities caused by construction activities on public housing estate using energy (electricity) consumption data. Households incurred marginal private costs in electricity consumptions when making short-term responses to negative externalities generated from adjacent construction activities. Third, we find no significant rebound effects in household electricity consumption behavior at the end of the construction activities.

The remainder of the paper is organized as follows: Section 2 reviews past studies of residential energy (electricity) consumption behavior. Section 3 provides background on residential electricity consumption and housing construction activities in Singapore. Section 4 describes data sources and empirical methodologies. Section 5 analyzes empirical results and draws necessary inference on households’ adjustment of dwelling comfort through increases in electricity consumption. Section 6 concludes by highlighting limitations of the study.

2. Literature Review

There are two strands of literature on residential energy consumption. The first strand of literature models energy consumption as a factor input into the production of comfort in dwelling (“purchased comfort”). Quigley (1984) and Quigley and Rubinfeld (1989) explicitly separate housing attributes that provide direct satisfaction to households, such as vintage, room arrangement and size, from attributes that use energy (electricity and gas) as inputs to the production of thermal comfort (“produced comfort”), such as furnaces and air-conditioners. Quigley (1984) tests the impact of energy price changes on demand for housing services and input factors using a sample of newly constructed dwelling, and finds that high energy prices induce “conservationism” in household energy consumption. Quigley and Rubinfeld (1989) show that high energy prices have a positive impact on housing prices and households choose to substitute housing vintage (attributes) for production input in housing services (energy consumption). The elasticity of substitution between “purchased comfort” (energy consumption) and “produced comfort” (demand for comfort) is stronger in Metropolitan Statistical Areas (MSAs) with extreme climates.

Like the demand model for housing services proposed by Quigley and Rubinfeld (1989), three broad categories of factors are expected to influence electricity demand by households, which include factor inputs for housing services production (energy consumption and installation of air-conditioner and furnace), housing attributes (vintage and design), and climatic factors. On the energy costs (inputs), Fisher and Kaysen (1962) show that households do not significantly adjust their electricity consumption in relation to changes in electricity price, but variations in electricity consumption are observed among households with different income. Wilson (1969) and Anderson (1972) find that electricity prices, income and gas prices are jointly significant in determining electricity demand. Halvorsen (1975), however, rejects the inelastic electricity consumption hypothesis, and find a strong direct price elasticity of demand with respect to electricity price that is near unity, but a weak and insignificant cross-elasticity of demand with respect to gas prices.

The second strand of literature examines how households change their electricity consumption behavior in reacting to exogenous interventions, such as price shocks (Halvorsen, 1975; Dubin, Miedema and Chandra, 1986; and Reiss and White, 2005, 2008; and others), public pressure (Reiss and White, 2008), "environmentalism" ideology (Kahn, 2007; Costa and Kahn, 2011, 2013), energy-saving home improvement (Metcalf and Hassett, 1999) and changes to building codes (Costa and Kahn, 2010; Jacobsen and Kotchen, 2013).

Reiss and White (2005) show significant skewness in the distributions of price elasticity in residential electricity demand using the micro-data of 1,300 Californian households. They find that the non-linear pricing structure of electricity tariffs intended to promote energy conservation in California has attracted different behavioral responses of households with different income levels. They find that high income households and households with high electricity consumption are less sensitive to changes in electricity prices. Using the energy price spike in June 2000 and the subsequent price cap in California on households' electricity consumption as policy interventions, Reiss and White (2008) show that the electricity consumption dropped by 13% during the energy price spike periods, but the consumption rebounded by 8% when a price cap was imposed after a 60-day period controlling for the weather effects before and after the price changes. They also show that Californian households responded voluntarily to the public campaign appealing them to conserve energy during the price cap periods. Costa and Kahn (2013) find that the "voluntary restraint" in conserving energy is stronger in the liberal communities than in the conservative communities. Kahn (2007) also shows that the communities with a high proportion of the Green Party registered voters are more likely to adopt "green conspicuous consumption" of energy-efficient products. Public pressure to conserve energy is also more effective in the Green Party-dominated communities.

Changes to households' electricity consumption behavior could be transitory if energy prices fluctuate; and this phenomenon is referred to as the rebound effects. Long-term responses via input factor substitution are observed, if households invest in more energy-efficient furnaces and air-conditioners to maintain produced comfort levels.[7] However, Metcalf and Hassett (1999) and Dubin, Miedema and Chandran (1986) argue that investment returns in energy efficient technologies are excessively high. Metcalf and Hassett (1999) find that realized returns of investing attic installation are far lower than returns estimated by engineers and product manufacturers; they call the phenomenon an "energy paradox". Dubin, Miedema and Chandran (1986) affirm the results showing that the realized benefits of energy conservation is 13% below the engineering estimates for cooling and 8-12% below for heating. However, the two studies disagree on the rebound effects. Metcalf and Hassett (1999) find that households did not change the temperature setting on their thermostats after investing in attic installation. However, Dubin, Miedema and Chandran (1986) show that price elasticity is lower for households, who keep their houses warmer in summer and cooler in winter.

Costa and Kahn (2010) show that California's building codes first instituted in 1978 were only effective in lowering electricity consumption in houses built during the pre-code period and the period after 1983; but the impact was insignificant during the initial period of the introduction of the codes. They argue that the low electricity prices in the 1970s and the early 1980s (the initial periods of the introduction of the new codes) contributed to the inefficient building designs. In another study by Jacobsen and Kotchen (2013) using residential billing data on electricity and natural gas in the city of Gainesville, Florida, they find that buildings constructed after the 2001 energy codes are more energy efficient. They estimate that the energy code resulted in a 4% decrease in residential electricity consumption, and a 6.4% reduction in residential natural gas consumption. They also find that households' electricity consumption is less responsive to weather-induced demand shocks in the post code-change period.

7 Short run income and price effects are found to be weaker than long term effects on electricity consumption (Dodgson, Millward, and Ward, 1990; Holtedahl and Joutz, 2004; Kamerschen and Porter, 2004; Moral-Carcedo and Vicéns-Otero, 2005).

Household energy consumption can be influenced by climatic changes, such as increases in the number of hot or cool days (Grimmond, 2007). Quigley and Rubinfeld (1989) find that significant variations in energy consumption ("purchased comfort") in different MSAs. Households in cities with extreme climate, such as Washington, Kansas City, Chicago, Minneapolis and Milwaukee, consumed more energy ("comfort") than households in coastal cities with mild climate, such as Seattle, Portland, San Diego, San Francisco and Los Angeles. Their results also show that dwelling in cities with mild climate are substantially more expensive than those located in warm or cold climate holding other things constant.

In testing households' behavioral responses to price effects, finding good instruments to control for endogeneity in energy prices and demand is one main obstacle. Building code changes are not necessarily independent from energy price effects, though some studies show that buildings in the post-code change period have adopted more energy-efficiency designs (Costa and Kahn, 2013). Do households in the same community embrace the same environmental ideology? Do liberals practice more voluntary restraints or simply have lower demand for comfort? These are confounding factors that may possibly taint the outcomes on households' demand for comfort.

In this study, we do not observe the actual demand for "comfort" of heterogeneous households, but we use construction activities to identify marginal changes in "produced comfort" in housing services for households living in adjacent housing estates. Construction noise and pollution deteriorate the comfort level; and households increase "purchased comfort" via air-conditioning indoor environment to mitigate negative impact on their dwelling comfort. If construction noises induce more electricity consumption by households, we should only observe marginal increases in electricity bills for households in housing estates that are close to construction sites; and no changes to electricity bills for households, who are not affected by construction activities keeping weather and housing attributes constant.

3. Construction Activities and Electricity Consumption in Public Housing Estates in Singapore

3.1. Public housing in Singapore

The Housing and Development Board (HDB) established in 1960 is the public housing authority of Singapore entrusted with the responsibilities of building affordable housing for

Singaporean citizens. After more than half a century of intensive public housing program, HDB has been able to fulfill the homeownership aspiration of more than 90% of the Singaporean households. Today, public housing stock makes up nearly 80% of the total housing stocks in Singapore, whereas the remaining 20% housing stocks are developed by private developers. With more than 90% of the population owning their houses as in 2013, Singapore has one of the highest home ownership rates in the world.

Public housing, or more commonly known as HDB housing, is a form of subsidized housing in Singapore, which is built by the government and allocated to Singaporean citizens, who meet the monthly income ceiling of S$12,000 per household.[8] The social-economic attributes of households living in public housing are representative of the majority population of Singapore. Private housing buyers, who come mainly from the high and medium income groups in the society, have significantly different socio-economic attributes.

A typical HDB town is planned as a compact and self-sustained town comprising a nexus of neighbourhoods and precincts organized in a hierarchical order by size of developments. There are currently 26 HDB towns in Singapore with varying size. A bigger town is made up of as many as nine neighbourhoods, whereas a smaller town is formed by only two neighbourhoods. Each neighbourhood is subdivided into smaller planning areas known as precincts and served by a commercial neighbourhood center. A precinct comprises a cluster of about ten vertical blocks of public housing flats on average; and few precincts are then collectively organized into a neighbourhood. The HDB building program is usually planned at the precinct level, and buildings are built in clusters across the island. Some degrees of homogeneity in the design of HDB are observed with a precinct. Buildings in different precincts and neighborhoods could vary in design and depending on the years they were built.

Public housing is usually designed by in-house architects of HDB, but built by private contractors/builders. HDB adopts the pre-fabrication construction technique because of economics of scale in construction and short delivery time for public housing projects. The pre-fabrication process requires a high degree of standardization in building design, floor plans and material used. Unlike housing built by private developers, which are more diverse in terms of

[8] The income ceiling has been revised from S$8,000 per month to S$10,000 per month with effects from 15 August 2011, and then to S$12,000 with effects from 24 August 2015.

quality and price, building attributes, such as window size and façade, are more homogeneous in public housing. Therefore, we could rely on public housing block level data to design a clean quasi-experiment to test households' responses to changing externality effects caused by construction nose. Our results are less likely to be affected by possible unobserved variations in building related characteristics.[9] Furthermore, we also include district level and/or postal code level fixed effect in our models to control for spatial differences across HDB precincts and neighbourhoods.

3.2. Construction activities

Singapore, like many densely-built tropical cities, experiences a local climatic phenomenon known as urban heat island (UHI) effects.[10] UHI effects in Singapore cause temperatures to vary up to 7°C between the morning and the evening (several hours after sunset) hours, and 4°C between the urban and the non-urban vegetated areas (Chow and Roth, 2006; Priyadarsini, Wong and Cheong; 2008). UHI effects are more severe in housing estates located near construction sites, where noise and air pollutions generated by construction activities cause deterioration to the quality of indoor living environment. Strict enforcement of construction noise controls is necessary to mitigate negative externalities from construction activities. In Singapore, the Environmental Protection and Management (Control of Noise at Construction Sites) (EPM) Regulations[11] are enacted to regulate works carried out at the construction sites, which are specifically defined as:

a) the erection, construction, alteration, repair or maintenance of buildings, structures or roads;
b) the breaking up, opening or boring under any road or adjacent land in connection with the construction, inspection, maintenance or removal of works;
c) piling, demolition or dredging works; or
d) any other work of engineering construction;

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9 Due to inaccessibility to private housing data, we are not able to compare different electricity consumption behaviour of families living in public housing versus those in the private housing. We are also not able to test the differential effects of design and building attributes between the two housing types in our studies on electricity consumption.

10 Urban heat island (UHI) is a phenomena where built-up city areas experience warmer temperature than outlying rural areas (Oke, 1982; Stone and Rodgers, 2001).

11 These regulations denoted as "G.N. No. S 157/1999" have been enacted and revised in 2008 under the "Environment Pollution Control Act" (Chapter 94A, Section 77). The regulations spell out the permissible noise levels and the time for works in a construction site. A penalty of up to S$40,000 could be imposed, if a developer fails to comply with the permissible noise levels, and $1,000 for every day thereof during which if the non-compliance persists after conviction.

The Building Construction Authority (BCA), a government agency under the Ministry of National Development (MND), approves construction plans and regulates construction activities in Singapore. Singapore is a rapidly urbanized city state with a robust construction sector, which contributes S$35.2 billion, or an equivalent of 11.2%, to Singapore's GDP as of 2011. Construction activities that include construction of new residential and commercial buildings, demolition of old buildings, infrastructure and engineering projects, institutional buildings such as schools, hospital and community buildings, are carried out across the island state all year round. In 2011 alone, BCA received 6,228 building plan applications and issued 7,089 construction permits (BCA, 2012).

3.3. Residential Electricity Consumption

In Singapore, residential electricity consumption accounts for 15% of the overall electricity demand, which is the third largest user of electricity after the industry (40.2%) and the commerce and services (37.5%) sectors. During the period from 2009 to 2011, the total residential electricity consumption increased from 6,514 gigawatt hours (GWh) to 6,560 GWh, but the monthly average electricity consumption per household dropped from 481 kilowatt hours (kWh) in 2009 to 470 kWh in 2011.[12] Private households, which form about 18% of the total households in Singapore, consumed a monthly average of 784 kWh of electricity per month. The number is two times higher than the electricity consumption by households living in public housing units (369 kWh).

Singaporean households use the bulk of electricity for ventilation and cooling purposes. Air conditioners and refrigeration appliances account for nearly two third of the household electricity bills. The number is higher than that observed in a typical office building, which uses only 40% of its electricity on average for air-conditioning ("produced comfort") purpose (Ang, Goh, and Liu, 1992; Lee and Rajagopalan, 2008). Figure 1 show that the electricity consumption by households in Singapore is correlated with the mean temperature on the island. Electricity demand hits the peaks during the months from May to July when the mean temperature is the highest in a year.

[Insert Figure 1 here]

12 The statistics are obtained from the annual report 2012 by the Energy Market Authority (EMA) of Singapore.

4. Data and Experiment Design

4.1. Identification Strategy

In the absence of noise contour maps, it is difficult to accurately measure noise effects from different construction sites. In the transport and engineering literature, distance from noise sources has been widely used as a proxy for noise effects. The decibel (noise) intensity declines as we move further away from noise sources. In our identification strategy, we use the 1km radius from construction sites as a reasonable upper bound to define the boundary of construction noise externalities. In this setup, we assume that HDB housing blocks are unlikely to be 'affected' by negative externalities, if they are located outside 1km range from a construction site. Based on the 1km radius, we are able to match a total of 42 construction projects to 1,800 HDB housing blocks in our sample.

The impact of construction noise is correlated with the scale of construction projects, which could be measured by the gross floor areas for each project. When we test the marginal effects of different distance bands of 0.1 km interval within the boundary of 1km radius from the construction noise on electricity consumption, we find that 500 meter appear to be a cut-off for noise effects beyond which the negative impact diminishes. Based on the results, we thus propose to use the two-tier distance identification to sort HDB housing blocks into a treatment groups (denoted as "treated" in the empirical models), and a "control" group. For smaller construction project of less than 5000 square meters (sqm), the radius of 500 meters is used; whereas for large scale projects with gross floor areas exceeding 5000 sqm, the 1km radius is used to identify the treatment housing samples. The scale adjustment takes into account both intensity and distance (boundary) of negative impact generated from construction activities.

4.2. Quasi-Experiment Design

We design a quasi-experiment to explicitly test two questions relating to household behaviors in electricity consumptions: 1) Do households consume more electricity ("purchased comfort") by closing windows and air-conditioning their indoor space in response to noise pollution (negative externalities) from nearby construction activities? 2) Is there a rebound effect in electricity consumption behavior of affected residents in the post-construction period?

Singaporean households could use fans and air conditioners and close their windows to keep noise and heat out from the indoor environment. By changing the ventilation strategy, they incur higher costs for the "purchased comfort", which are reflected in rising electricity bills during the months when construction activities are carried out in the adjacent sites. However, some households, who choose not to use the expensive ventilation strategy, endure the lower "produced comfort" in their indoor environment by using the natural ventilation without increasing air-conditioning costs.

4.3. Empirical Data

We obtain the monthly electricity consumption data for a large sample of HDB (public) housing blocks for the period from 2009 to 2011 from the National Environmental Agency (NEA), a Singapore's government agency that is responsible for enforcing the EPM regulations. We use the block-level monthly electricity consumption data as the outcome variables, and calculate the distance of each HDB block to the nearest construction site using geographic information system (GIS) software. The HDB housing blocks are sorted into the treatment group, if they are located within a radius of 500 meters to 1000 meters to construction sites, and otherwise, they are sorted into the "control" group. We could also identify each of the public housing blocks using a unique six-digit postal code.

Figure 2 shows the distributions of average monthly electricity consumption for the 3-year period from 2009 to 2011. The average electricity consumption is estimated at 50,265 KWh for the sample of 5,321 HDB housing blocks in Singapore. We use the Getis-Ord Gi* tool in ArcGIS 10 (ESRI) to plot the high- and low-value clusters by percentage change in electricity consumption at the block-level across the years. Figure 3 shows that the strongest clusters with positive changes (year on year increases) in electricity consumption are mainly found in the northern and eastern regions of the island. We use the district and postal code fixed effects to control for spatial clustering and heterogeneity effects in our empirical model.

[Insert Figures 2 and 3 here]

Table 1 shows the summary statistics of electricity consumption by region in Singapore for the period 2009-2011. The results show that the mean electricity consumption is the highest in 2010 compared to 2009 and 2011. By region, we find that the mean electricity consumption in the Central Region is the highest; whereas the Eastern Region has the lowest mean electricity consumption in the 3-year period.

[Insert Table 1 here]

The second data source on construction activities in Singapore between 2009 and 2011 is obtained from the construction database of the Building Construction Authority (BCA). The database covers all major types of construction activities, such as residential, commercial, industrial and public infrastructure works. After removing infrastructure projects, building upgrading and alteration works, our final samples contain 322 construction activities involving erection of at least one building identifiable by a distinct postal code. Figure 4 shows the distributions of the construction activities during the period 2009-2011.

[Insert Figure 4 here]

4.4. Empirical Model Design

The HDB housing blocks provide a natural experiment to test if residents living close to construction sites increase electricity consumption ("purchased comfort") in order to mitigate negative externalities generated by nearby construction activities. We use the difference in differences (diff-in-diff) methodology [13] to test if construction externality could have differential impact on the electricity consumption between the treatment group and the control group. In our quasi-experiment setting, construction sites are randomized sources of noise externality. We use both spatial and temporal variations in the block-level electricity consumptions (responses) to test causal relationships of noise sources and electricity consumption. We also test differences between household's electricity consumption during (at the start of) and after a construction event.

First, we run a base regression model with the log of electricity consumption at the block-level as the dependent variable controlling for the unobserved spatial heterogeneity using a fixed district effect variable (λ_i), and the month of the year variations using a fixed time effect variable (τ_t). The ordinary least squares (OLS) regression equation is represented as:

$$Log(Con_{it}) = \alpha_1 + \beta_1 "Treated" + \lambda_{1i} + \tau_{1t} + \varepsilon_{1it} \tag{1}$$

[13] The diff-in-diff methodology has been as an increasingly popular way to estimate causal relationships (Bertrand, Duflo and Mullainathan, 2004). It has been widely used in recent years to test various treatment effects, such as environmental conservation and energy consumption, in quasi-experiment settings. The simplicity of the method is one of the draws of the diff-in-diff method, but the main appeal lies with its ability to circumvent endogeneity when comparing behaviour of heterogeneous individuals in the quasi-experiment setting.

where α_i is an intercept term, ε_{it} is an *i.i.d* error term, and β_i is an estimated coefficient on the "Treated" variable, which has a value of 1, if a HDB housing block *i* is located within either 1km radius, or 500m radius from the nearest construction site with a gross floor area of less than 5000 square meters (sqm). We control for spatial variations in the block-level electricity consumptions using the postal and the district fixed effects in the models.

If [$\beta_1 > 0$] is not rejected, the result implies that households living in the "treated" blocks consume more electricity relative to the control group of households. We thus infer that households adjust their electricity consumption by using more air-conditioning to mitigate negative externalities during the construction period. As the attributes of HDB blocks are not available in our data, we use the block level (postal code) fixed effects, instead of the district fixed effect, to account for potential within-sample variations in consumption behavior for different HDB blocks. These may include regional socioeconomic differences (income and demographics) and building level differences (gross floor area, number of units, building material and age). The use of the block fixed effects (λ_i) gives the lower bound of the estimates for the marginal effects of the electricity consumption.

If the increase in electricity consumption is a "self-protection" mechanism in response to construction externalities, we should expect the consumption to revert back to the pre-construction level after construction works have been completed. The second model tests if permanent changes in electricity consumption behavior are observed for households living in "treated" blocks, after the construction activities have ceased at time C. The specification is written as:

$$Log(Con_{it}) = \alpha_2 + \beta_2 \times ["Treated" \times C] + \lambda_{2i} + \tau_{2t} + \varepsilon_{2it} \qquad (2)$$

where *C* is a dummy variable indicating time after the completion of construction activities, such that ["Treated"$\times$ *C*] has a value of 1, if a subject HDB block is identified jointly by the distance measure, i.e. within the 500m or 1km subject to the scale of construction, and the completion time dummy, *C*, which has a value of 1, if the time in month is after the completion of the construction works, [$t \geq C$]; and 0 otherwise. The spatial (district/building) and the time (month of the year) fixed effects are both controlled for in the model. If [$\beta_2 < 0$] is rejected, we find no "rebound" effect" as argued by Reiss and White (2008) indicating that electricity consumptions of households living close to construction sites do not revert back to the previous level, after construction externalities has been removed. The result also implies that the shift in households' electricity consumption is permanent.

Singapore is a country in the tropical climate zone with its daily temperatures varying only within a narrow range of about 6.7°C.[14] Based on the mean temperature distributions as in Figure 1, the hottest months are found between May and July of a year; but the temperatures are rarely more than 2°C compared to the cooler months between November and January of a year. While the small variations in temperature are not likely to have significant impact on productivity and economic growth as found in Graff Zivi and Neidell (2012); we could expect households to turn on air-conditioners for longer hours during the hottest months between May and July in a year. To test if the "persistence" effect is stronger in the hot months, we include an interactive variable "$Treated \times C \times hot$", where the "hot" dummy has a value of 1, if a month falls between May and July; and 0 otherwise. The extended model specification is given as:

$$Log(Con_{it}) = \alpha_1 + \beta_1 \times [\text{Treated}] + \beta_2 \times [\text{Treated} \times C] + \beta_3 \times [\text{Treated} \times C \times hot] + \lambda_{2i} + \varepsilon_{2it} \tag{3}$$

If [$\beta 3 \geq 0$] is not rejected, we expect the "persistence" effect to be stronger during the "hot" months relative to other months. Households are more likely to keep their electricity consumption behavior after the end of the construction activities; and they also use more electricity during the hot months relative to other months.

As Singapore is a highly urbanized city, where buildings are densely built and closely spaced in HDB estates in Singapore, it is important to ensure that spatial dependence in electricity consumption, if exists at block level, could be corrected. Anselin and Arribas-Bel (2013) argue that spatial dependence, if not removed, could potentially cause spurious results in OLS estimates.[15] Ross, Farmer and Lipscomb (2011) found that the spatial autocorrelation in the error term could not be effectively removed by measuring linear distances to (dis)amenity,

[14] Based on the daily means air temperature for the months in the period from 2009 to 2011, the difference between the maximum means and the minimum means is computed at about 6.7°c (Source: Department of Statistics).

[15] We thank one of the anonymous referees for highlighting the spatial dependence issue in the OLS estimator.

which are orthogonal to spatial fixed effects in the OLS models. We instead use the spatial panel data models proposed by Millo and Piras (2012) by adding a spatial lag of dependent variable and spatial autoregressive disturbances to Equation (1)[16]:

$$Log(Con_{it}) = \alpha_1 + \lambda(\mathbf{I_T} \otimes \mathbf{W_N})Log\left(Con_{i,t-1}\right) + \beta_1 "Treated" + \lambda_{1i} + \tau_{1t} + u_{it} \tag{4}$$

where $\mathbf{I_T}$ is an identity matrix of dimension T, $\mathbf{W_N}$ is an N×N spatial weights matrix of known constants with zero diagonal elements, and λ is the corresponding spatial parameters. The spatial autoregressive disturbances, u_{it}, could be decomposed into a time invariant component and a spatially autocorrelated innovations, ξ_{it}, which could be represented by an autoregressive process:

$$\xi_{it} = \rho(\mathbf{I_T} \otimes \mathbf{W_N})\xi_{i,t-1} + \upsilon_{it} \tag{5}$$

where ρ, such that ($|\rho| < 1$), is the spatial autoregressive parameter, ξ_{it} and υ_{it} are both iid error terms. The spatial lag and the spatial autoregressive disturbances could also be added to control for spatial dependence in Equations (2) and (3), respectively.

5. Empirical Results

The regressions in Table 2 test the differences in the block-level (geo-coded) electricity consumption between HDB households living close to construction sites ("treatment" group) and those that are not affected by construction noises ("control" group). The baseline OLS Model (1) shows that the estimated coefficient of 0.077 on the "treated" variable, which is a proxy for negative externalities of construction noise, is statistically and economically significant ($p < 0.05$). Construction activities increase the block-level electricity consumption of HDB households by 7.7% relative to those, who live outside 1km of the nearest construction sites (with gross floor area of more than 5,000 sqm) for the periods from 2009 to 2012. In Model (2) where we control for the fixed district effect and monthly changes (temporal), the coefficient on the construction externality effect is still positive and significant, but the magnitude reduces slightly to 6.9%. When we use the postal-code fixed effect (Model 3) to

16 We estimate the spatial panel data model using the R-package splm that is made available in the R Archive (http://CRAN.R-Project.org/package=splm).

control for unobserved building heterogeneity, the marginal effect of construction noise is still positive and statistically significant on the electricity consumption by block (6.0%).

Model 4 shows the results of the spatial panel data model indicating that the two spatial coefficients, Rho (ρ) and Lambda (λ), are highly significant. After controlling for the spatial dependence, the "treated" variable is still significant and positive, but the negative externality costs increase to 8.0%. Overall we find that households within HDB housing blocks consume more electricity in the same month of the year, if they live within 1km from large construction sites (>5,000 sqm).

[Insert Table 2 here]

Based on the average electricity consumption of 50,256 KWh per month during the period 2009-2011, we estimate an excess monthly electricity consumption of 3,015 KWh per block for households that are exposed to construction noises within 1km from their HDB housing blocks.[17] This translates into an annual figure of 36,184 KWh per block. In monetary terms, this externality is priced at about S$9,770 per block per annum, based on the electricity tariff of 0.27 cents per KWh as in 2009.[18]

Table 3 shows the results of the tests of a permanent shift in electricity consumption behavior of affected HDB households. The coefficient β_2 indicating the electricity consumption of the "treatment" HDB blocks after the completion of the construction activities is significant ($p <$ 0.05) and positive in both models. The OLS Model (6) estimates that the post-construction period electricity consumption of households in blocks located within 1km from large construction sites (>5,000 sqm) (or 0.5km for smaller construction sites) is 6.8% higher than that of households unaffected by the negative externalities. In OLS Model (7), we control for unobserved block level heterogeneity using the postal code fixed effects, the variations in the post-construction electricity construction are weaker, though the coefficient on "Treated × C" remains positive and significant at less than a 5% level. The results in Model (8), where spatially weights for the lag and the disturbance terms are controlled, show that the interactive

17 Based on an average electricity consumption for all blocks = 50,256.4 kWh, and the increases in electricity consumption of the treated blocks over untreated blocks (OLS model (3)) of 6.0%, the excess demand is computed at 3,015 KWh.

18 Source: The Annual Report of National Environmental Agency, 2009.

variable, (“Treated × C”) is significant and positive; and the coefficient increases significant to 9.1%. The results imply that the “treated” residents demand higher level of “comfort” in the post-construction periods relative to the control households. The “treatment” group of households did not adjust their electricity consumption back to the pre-construction level despite the removal of the negative externalities. In other words, there is a permanent shift in the electricity consumption behavior of the “treated” households in the post-construction periods.

[Insert Table 3 here]

We next test if seasonal variations in temperatures could influence households’ behavior in electricity construction after the end of the treatment effects. Table 4 shows that the coefficient β_3 on the interactive variable of “*Treated* $\times$ *C* $\times$ *hot*” is significant and positive in all three models. The inclusion of the new interactive has also no impact on on “*Treated*” and “*Treated* $\times$ *C*”, and the two coefficients, β_1 and β_2, remain significant and positive. The results imply that the persistence effects are stronger, if the construction activities end in the hot months of a year, relative to other months. Households are more likely to turn on their air-conditioner for longer hours in the hot months to keep their indoor environment cool, and the effects persist after the construction externalities are removed. Households affected by the construction externalities are less likely to switch back to natural ventilation to reduce discomfort in hot days compared to households that are not affected by the construction noise in the earlier periods. The results imply that the “treatment” effect on households is no longer just temporary responses to construction externalities; we expect households to be less adaptable to lower level of dwelling comfort after the end of construction. More empirical tests could be conducted, subject to availability of data, to verify if the results are correlated with the “habit persistence” story.

[Insert Table 4 here]

5.1. Robustness test

As robustness checks, we repeat the regressions using two sub-sample periods: 2009-2010 and 2010-2011 to test the structural validity of the previously estimated coefficients in Table 2. The robustness test results as summarized in Table 5 are robust under different specifications. For the sample periods 2009-2010, the results show that the coefficients on the "Treated" variable (β_1) are significant at less than a 1% level in Models (12) and (13), whereas, β_1 for the fixed building effect model in Model (14) is significant at less than a 10% level. After controlling for both the fixed district and the fixed time effects, the negative externalities of construction activities (the "treatment" effects) have weaker impact on the block-level electricity consumption in the sub-period 2010-2011 relative to the sub-period 2009-2010. However, when we rerun the models by using the fixed postal code effect to capture for unobserved spatial heterogeneity, the coefficient β_1 in the OLS Model (18) for the sub-period 2010-2011 is higher than that estimated using the sub-period 2009-2010 samples. The results in the two spatial panel models (Models 15 and 19), which are free of spatial dependence errors, show that the treatment effects remain significant and positive. Overall, the effects of construction activities on electricity consumption are significantly positive for households in both sub-samples, *ceteris paribus*.

[Insert Table 5 here]

Do the permanent shifts in electricity consumption behavior of affected households in the post-construction activities persist in the two sub-sample periods? Table 6 shows that during the post-construction periods, the results on the electricity consumption behaviors of the "treated" households are significantly different from those in the "untreated" blocks. For the sub-samples period 2009-2010, the coefficients on the "Treated×C" variable are positive and significant in all the OLS Models. For the models in the second sub-period 2010-2011, we find that in the two Models (24) and (25), where the fixed district and the fixed month effects are controlled for, the results are robust and the coefficients are statistically and economically significant. However, when unobserved block level heterogeneity is controlled for in Model (26), the treatment effects (0.002) are still positive, but statistically insignificant in the sub-period 2010-2011. The results imply that even after the externalities have been removed (upon the completion of construction works), households in the treated block still consume between 7.7% and 8.3% more electricity than households living in the control HDB housing blocks after controlling for the district and the temporal variations. The results are also reaffirmed by the models adjusted for the spatial autocorrelated terms (Models 23 and 27), where the post-construction persistent effects remain significant at 10.6% and 11.8% for the two sub-sample periods: 2009-2010 and 2010-2011, respectively.

[Insert Table 6 here]

6. Discussions and Implications

This study makes three contributions to the literature on household energy consumption and environmental externalities. First, while households are sensitive to energy costs and non-linear pricing strategies (Reiss and White, 2005 and 2008), they would also adjust their "consumed comfort" when their indoor environment ("demand for comfort"), which is an element of the housing service utilities (Quigley and Rubinfeld, 1989), is deteriorated by external pollutions (negative externalities). This contributes to the previous studies that use building energy code changes (Costa and Kahn, 2010; Jacobsen and Kotchen, 2013) and political ideology (Kahn, 2007; Costa and Kahn, 2013) as exogenous interventions to test household electricity consumption behavioral changes. Second, based on increases in the energy expenses of households living close to construction sites, we provide an indirect but objective valuation of negative externality costs using actual outcomes, rather than hypothetical scenarios in some stated preference surveys.

The evidence on rebound effects has been mixed in the energy literature. Reiss and White (2008) find significant rebound effects in electricity consumption of Californian households, when a price cap was imposed in the fall of 2000. However, Dubin, Miedema and Chandran (1986) and Metcalf and Hassett (1999) find no rebound effects, where they show that installation of energy efficient appliances did not reduce the effective price of comfort. Instead, households increase energy usage to provide additional comfort. Third, we find no significant rebound effect in electricity consumption of households after the removal of the construction externalities. We instead find significant persistence in the electricity consumption behavior of households affected by construction noises. The persistence in their electricity consumption is also time-dependent. We observe significant restraints by households in their electricity construction, if the construction works ended in the sub-period 2010-2011. However, a positive coefficient is observed, if construction externalities have been removed earlier in the sub-period 2009-2010.

There are significant policy implications in terms of regulating, mitigation and compensation for negative environmental externalities. First, the Environmental Protection and Management

(Control of Noise at Construction Sites) Regulations (revised edition 2008) are enacted to regulate and monitor noise levels at construction sites in Singapore. Under the regulations, the Singapore's government sets noise limits, while the industry is given the "*flexibility to adopt solutions to minimise noise, and avoids imposing undue cost on the construction industry*."[19] For socially responsible construction firms, they will take necessary mitigating measures, such as site boarding, and adopt advance construction technology and equipment to reduce environmental risk and noise. However, if construction noise and pollution still persist, households may have to resort to other self-protection mechanism, such as shutting off indoor environment to eliminate the effects of construction noise. If regulations are not punitive enough to eliminate externalities from builders' actions, the "self-protection" by households could aggravate moral hazard in builders as argued by Ehrlich and Becker (1972).

Lastly, externality costs of construction activities on households, which work out to be S$9,770 per annum per block, are economically significant. Compensating households affected by construction noise may be socially just and equitable, but may not be an efficient solution (Alexandre, Barde, and Pearce, 1980). Colwell (1997) proposes a tender offer system to quantify the compensation for injury and sufferance of environment noises by households, which could reduce distributional effects of the negative externality. We calculate only one cost (increased electricity consumption) resulting from nearby construction works. Households may also claim additional costs related to negative health or psychosocial effects. The "persistence" in electricity consumption behavior of households imposes high economic costs, because they are adapted to new indoor comfort levels that could only be "sustained" with higher electricity costs (air-conditioners).

7. Conclusion

This study uses a unique dataset of electricity consumption by public housing residents in Singapore measured at the block (building) level. The data covering the periods from 2009 to 2011 are used in our quasi-experiment of households' electricity consumption behaviours. We use the two-tiered distance measure, which is represented by a dummy that has a value of 1, if a sample housing block is located within 500m from a construction site with less than 5000

[19] The comments by the Senior Parliamentary Secretary (Environment and Water Resources), Dr Amy Khor were reported in the Straits Times, "Construction noise: Big rise in complaints", 10 February 2009.

sqm of gfa, or 1km for a larger scale construction project of above 5000 sqm gfa; and 0 otherwise, to proxy the construction noise externality. Based on the distance dummy, we sort the housing blocks into a treatment group and a control group, and test if different responses in term of electricity consumption are observed between the two groups, when they are subject to construction externalities.

We run the diff-in-diff regressions and show that there are significant increases in electricity consumptions by households living close to construction sites. The increases in electricity consumption induced by negative externalities caused by construction noises are estimated at about 6.0% relative to those unaffected ("control") households, after controlling for the fixed building and fixed month of the year effects in our models. The costs of negative externalities are economically significant, which are estimated at about S$9,770 per annum for each affected HDB block, based on the average monthly consumption of 50,256 KWh per block and an electricity tariff of 0.27 cents (National Environmental Agency, 2009). In term of per household electricity consumption, the marginal increase of 30.15 kWh is equivalent to about 16.4% increases in the electricity consumption for a typical 2-room flat, or 8.1% for a typical 4-room flat (source: Singapore Power Limited).

We also find that the increases in electricity consumption of the affected households are persistent. Households' electricity consumption did not revert back to the pre-construction levels after the removal of the negative externality. They consume more electricity than other households living outside 1km radius of construction sites, even after the completion of the construction activities. The results do not support the "rebound" effects observed in Reiss and White (2008). The persistence in electricity consumption caused by construction externalities imposes high economic costs on households, who are adapted to new air-conditioned indoor comfort.

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Table 1: Descriptive statistics of electricity consumption in Singapore between 2009-2011

			Analysis Variable : Consumption (Kwh)			
Region	**Year**	**Number of Observation**	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Central Region	2009	11664	49571.06	23876.01	10395	715198.
	2010	11664	50450.64	24891.51	10049	737782
	2011	11664	48823.08	25414.89	10191	788391
East Region	2009	9912	45937.13	20339.66	10078	289663
	2010	9912	46862.72	20257.78	10189	275511
	2011	9912	45492.57	19645.6	10217	264910
North East Region	2009	4260	48979.54	15305.59	11579	191071
	2010	4260	49961.03	15372.3	11611	193290
	2011	4260	48474.87	15357.41	11023	196434
North Region	2009	11148	46277.05	13584.29	10283	251219
	2010	11148	47282.61	13706.95	10810	239178
	2011	11148	46175.47	13873.94	10059	266071
West Region	2009	18804	47145.73	15307.23	10012	219896
	2010	18804	47788.29	15285.33	10096	213725
	2011	18804	46314.28	15058.45	10189	211041

Note: *The table reports the descriptive statistics of electricity consumption in kWh, which include mean, standard deviation, minimum and maximum numbers. The numbers HDB block samples are also shown in the Table. The results are also computed by region, where Singapore is broadly divided into five planning regions, such as Central, East, North East, North and West.*

Table 2: Household Behavior in Electricity Consumption for the period 2009-2011

Dependent variable: Log (consumption)	**Model (1)** OLS	**Model (2)** OLS	**Model (3)** OLS	**Model (4)** Spatial Panel
Intercept	10.680***	10.65***	10.37***	15.435***
	(0.001)	(0.008)	(0.018)	(0.037)
Treated	0.077***	0.069***	0.060**	0.080***
	(0.001)	(0.002)	(0.026)	(0.003)
Rho (ρ)				0.629***
				(0.003)
Lambda (λ)				-0.438***
				(0.005)
Time fixed effects	NO	YES	YES	YES
District fixed effects	NO	YES	NO	YES
Postal Code Fixed effects	NO	NO	YES	NO
Observations	168,552	168,552	168,552	165,096
Adj. R^2	0.010	0.120	0.900	n.a.

*Notes: The table reports the regression results estimated using OLS for the full samples of HDB blocks. The dependent variable is electricity consumption per block per month. We use "Treated" to identify HDB block that are located within 1km,if construction projects in the neighboring location have gross floor areas of more than 5000 sqm, if the gross floor areas are less than 5,000 sqm. Except for the baseline Model (1), we control for fixed postal-code, fixed time, and fixed district effects in other models. In Model (4), we use spatial panel data model with fixed effects (using splm in an R package) developed by Millo and Piras (2012) to adjust for spatial auto-correlated disturbances. The splm model is estimated using the Maximum Likelihood (ML) estimator, and the adjusted R^2 is not provided (n.a.). Rho (ρ) and Lambda (λ) are the spatial autoregressive parameter for the dependent variable and the error term, respectively as in Equations (4) and (5). The t-statistics are given in parentheses; *** indicates significance at the 1% level; ** indicates significance at the 5% level; * indicates significance at the 10% level.*

Table 3: Tests of Persistence Effects in Electricity Consumption

Dependent variable: Log (consumption)	Model (5) OLS	Model (6) OLS	Model (7) OLS	Model (8) Spatial Panel
Intercept	10.72***	10.67***	10.43***	15.377***
	(0.002)	(0.010)	(0.019)	(0.021)
Treated × C	0.049**	0.068***	0.003**	0.091***
	(0.003)	(0.004)	(0.001)	(0.009)
Rho (ρ)				0.631***
				(0.005)
Lambda (λ)				-0.429***
				(0.008)
Time fixed effects	NO	YES	YES	YES
District fixed effects	NO	YES	NO	YES
Postal Code Fixed effects	NO	NO	YES	NO
Observations	58,212	58,212	58,212	56,340
Adj. R^2	0.003	0.110	0.890	n.a.

*Notes: The table reports the regression results estimated using OLS for the samples of HDB blocks that are affected by construction activities ("treated" samples). The dependent variable is electricity consumption per block per month. We use "Treated × C" to indicate differentiate the effects before and after the completion of the construction activities, where "C" denotes the end of construction works, and the "Treated" denotes the HDB block that are located within 1km, if construction projects in the neighboring location have gross floor areas of more than 5000 sqm, if the gross floor areas are less than 5,000 sqm. Except for the baseline Model (5), we control for fixed postal-code, fixed time, and fixed district effects in other models. In Model (8), we use spatial panel data model with fixed effects (using splm in an R package) developed by Millo and Piras (2012) to adjust for spatial auto-correlated disturbances. The splm model is estimated using the Maximum Likelihood (ML) estimator, and the adjusted R^2 is not provided (n.a.). Rho (ρ) and Lambda (λ) are the spatial autoregressive parameter for the dependent variable and the error term, respectively as in Equations (4) and (5).The t-statistics are given in parentheses; *** indicates significance at the 1% level; ** indicates significance at the 5% level; * indicates significance at the 10% level.*

Table 4: Seasonal and Persistence Effects on Electricity Consumption

Dependent variable: Log (consumption)	Model (9) OLS	Model (10) OLS	Model (11) OLS
Intercept	10.68***	10.74***	10.45***
	(0.001)	(0.006)	(0.022)
Treated	0.041**	0.024***	0.052*
	(0.002)	(0.003)	(0.031)
Treated × C	0.043***	0.054***	0.011***
	(0.003)	(0.003)	(0.001)
Treated × C × hot+	0.115***	0.123***	0.095***
	(0.007)	(0.007)	(0.002)
Time fixed effects	NO	NO	NO
District fixed effects	NO	YES	NO
Postal Fixed effects	NO	NO	YES
Observations	168,552	168,552	168,552
Adj. R^2	0.014	0.086	0.857

Notes: The table reports the regression results estimated using OLS for the samples of HDB blocks that are affected by construction activities ("treated" samples). The dependent variable is electricity consumption per block per month. We use "Treated × C" to indicate differentiate the effects before and after the completion of the construction activities, where "C" denotes the end of construction works, and the "Treated" denotes the HDB block that are located within 1km, if construction projects in the neighboring location have gross floor areas of more than 5000 sqm, if the gross floor areas are less than 5,000 sqm. We use Treated × C × hot to represent hot months of construction periods. *Except for the baseline Model (9), we control for fixed postal-code, fixed time, and fixed district effects in other models. The t-statistics are given in parentheses; *** indicates significance at the 1% level; ** indicates significance at the 5% level; * indicates significance at the 10% level.*

+ Hot months include dummy for may June and July (see Figure 1).

Table 5: Sub-period Analyses of Household Behavior in Electricity Consumption

	Sample period: 2009-2010				Sample period: 2010-2011			
Dependent variable:	Model (12)	Model (13)	Model (14)	Model (15)	Model (16)	Model (17)	Model (18)	Model (19)
Log (consumption)	OLS	OLS	OLS	Spatial Panel	OLS	OLS	OLS	Spatial Panel
Intercept	10.68***	10.72***	10.45***	15.419***	10.68***	10.65***	10.34***	15.475***
	(0.001)	(0.009)	(0.021)	(0.044)	(0.001)	(0.009)	(0.005)	(0.045)
Treated	0.0786***	0.070***	0.055*	0.081***	0.076***	0.06***	0.078***	0.079***
	(0.002)	(0.002)	(0.030)	(0.004)	(0.002)	(0.002)	(0.033)	(0.004)
Rho (ρ)				0.625***				0.632***
				(0.004)				(0.003)
Lambda (λ)				-0.436***				-0.439
				(0.006)				(0.006)
Time fixed effects	NO	YES	YES	YES	NO	YES	YES	YES
District fixed effects	NO	YES	NO	YES	NO	YES	NO	YES
Postal Code Fixed effects	NO	NO	YES	NO	NO	NO	YES	
Observations	112,368	112,368	112,368	110,064	112,368	112,368	112,368	110,064
Adj. R^2	0.011	0.120	0.900	n.a.	0.011	0.120	0.890	n.a.

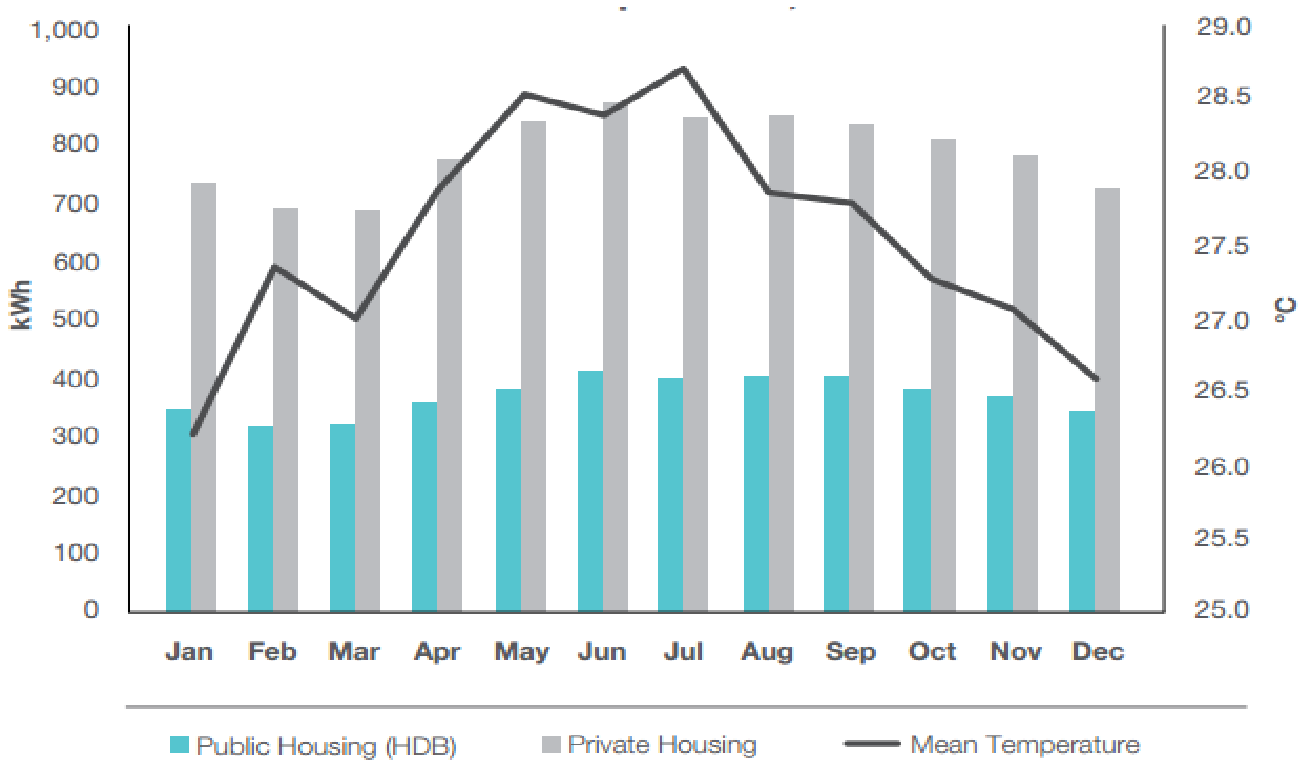
*Notes: The table reports the regression results estimated using OLS for the full samples of HDB blocks. The dependent variable is electricity consumption per block per month. We use "Treated" to identify HDB block that are located within 1km,if construction projects in the neighboring location have gross floor areas of more than 5000 sqm, if the gross floor areas are less than 5,000 sqm. Except for the baseline Models (12) and (16), we control for fixed postal-code, fixed time, and fixed district effects in other models. In Models (15) and (19), we use spatial panel data model with fixed effects (using splm in an R package) developed by Millo and Piras (2012) to adjust for spatial auto-correlated disturbances. The splm model is estimated using the Maximum Likelihood (ML) estimator, and the adjusted R^2 is not provided (n.a.). Rho (ρ) and Lambda (λ) are the spatial autoregressive parameter for the dependent variable and the error term, respectively as in Equations (4) and (5). The t-statistics are given in parentheses; *** indicates significance at the 1% level; ** indicates significance at the 5% level; * indicates significance at the 10% level.*

Table 6: Sub-period Analyses of Persistence Effects in Households' Electricity Consumption

	Sample period: 2009-2010				**Sample period: 2010-2011**			
Dependent variable: Log (consumption)	Model (20) OLS	Model (21) OLS	Model (22) OLS	Model (23) Spatial Panel	Model (24) OLS	Model (25) OLS	Model (26) OLS	Model (27) Spatial Panel
Intercept	10.72***	10.73***	10.51***	15.341***	10.71***	10.65***	10.43***	15.378***
	(0.002)	(0.011)	(0.022)	(0.022)	(0.004)	(0.013)	(0.024)	(0.023)
Treated × C	0.0779***	0.083***	0.007***	0.106***	0.0512***	0.077***	0.002	0.118***
	(0.003)	(0.004)	(0.002)	(0.009)	(0.005)	(0.006)	(0.002)	(0.014)
Rho (ρ)				0.623***				0.635***
				(0.006)				(0.006)
Lambda (λ)				-0.424***				-0.434
				(0.010)				(0.009)
Time fixed effects	NO	YES	YES	YES	NO	YES	YES	YES
District fixed effects	NO	YES	NO	YES	NO	YES	NO	YES
Postal Fixed effects	NO	NO	YES	NO	NO	NO	YES	NO
Observations	38,808	38,808	38,808	37,560	38,808	38,808	38,808	37,560
Adj. R^2	0.011	0.11	0.9	n.a.	0.11	0.11	0.89	n.a.

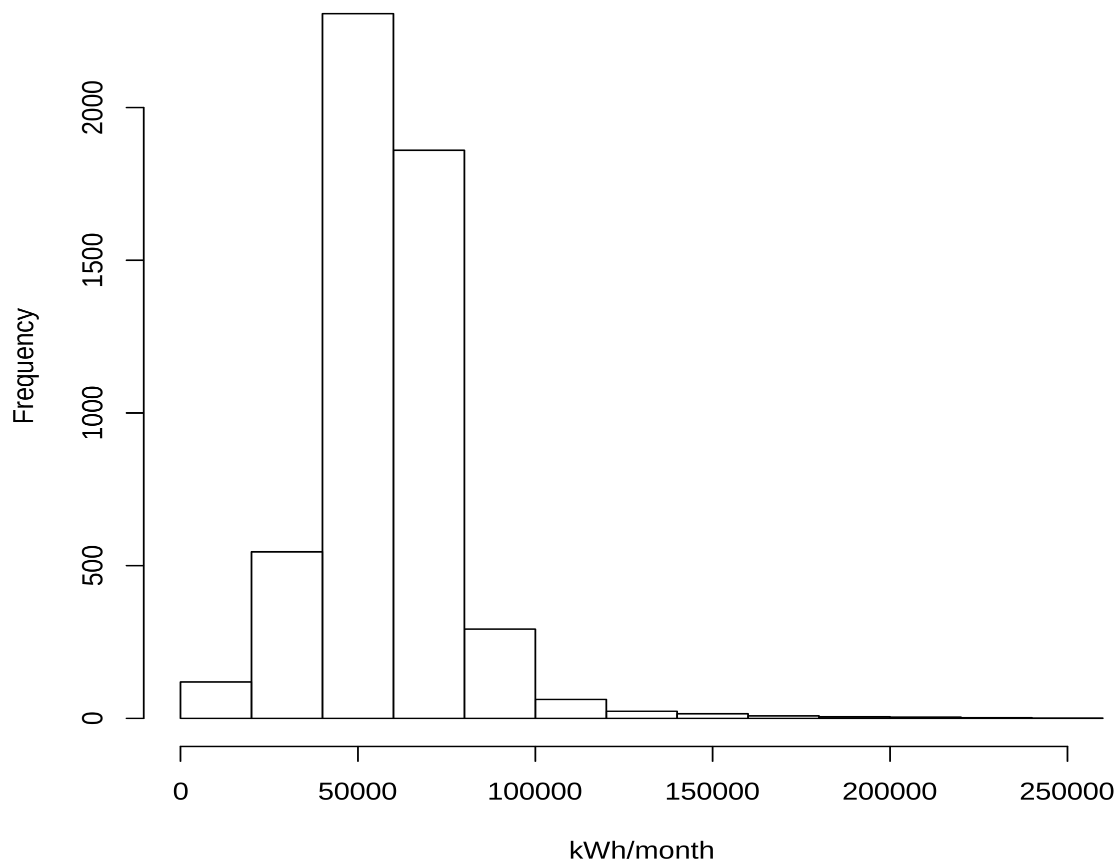
*Notes: The table reports the regression results estimated using OLS for the samples of HDB blocks that are affected by construction activities ("treated" samples). The dependent variable is electricity consumption per block per month. We use "Treated × C" to indicate differentiate the effects before and after the completion of the construction activities, where "C" denotes the end of construction works, and the "Treated" denotes the HDB block that are located within 1km, if construction projects in the neighboring location have gross floor areas of more than 5000 sqm, if the gross floor areas are less than 5,000 sqm. Except for the baseline Models (20) and (24), we control for fixed postal-code, fixed time, and fixed district effects in other models. In Models (23) and (27), we use spatial panel data model with fixed effects (using splm in an R package) developed by Millo and Piras (2012) to adjust for spatial auto-correlated disturbances. The splm model is estimated using the Maximum Likelihood (ML) estimator, and the adjusted R^2 is not provided (n.a.). Rho (ρ) and Lambda (λ) are the spatial autoregressive parameter for the dependent variable and the error term, respectively as in Equations (4) and (5). The t-statistics are given in parentheses; *** indicates significance at the 1% level; ** indicates significance at the 5% level; * indicates significance at the 10% level.*

Figure 1: Average Monthly Electricity Consumption and Temperature, 2011



Note: The figure plots the mean temperature (dark line) in ℃ (as measured by the right Y-axis) and the average monthly electricity consumption of households living in public HDB housing (grey column) and private housing (light blue column) (as measured in KWh). Source: Energy Market authority (EMA) Report, 2012 ([http://www.ema.gov.sg/media/files/publications/EMA_SES_2012_Final.pdf.)](http://www.ema.gov.sg/media/files/publications/EMA_SES_2012_Final.pdf)

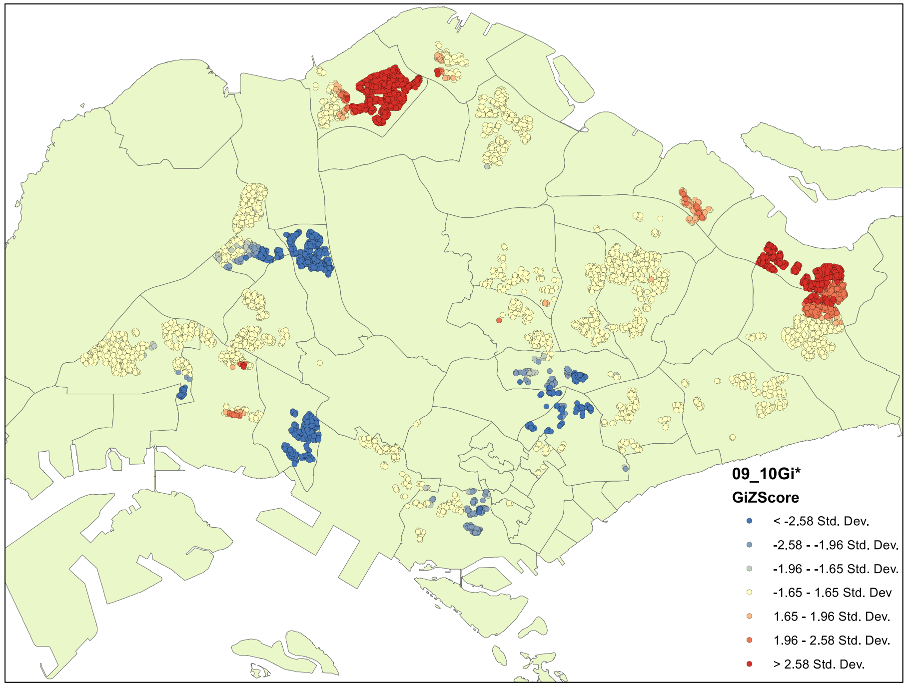
Figure 2: Distribution of Block-Level Average Monthly Electricity Consumption for HDB Blocks in Singapore (2009 – 2011)



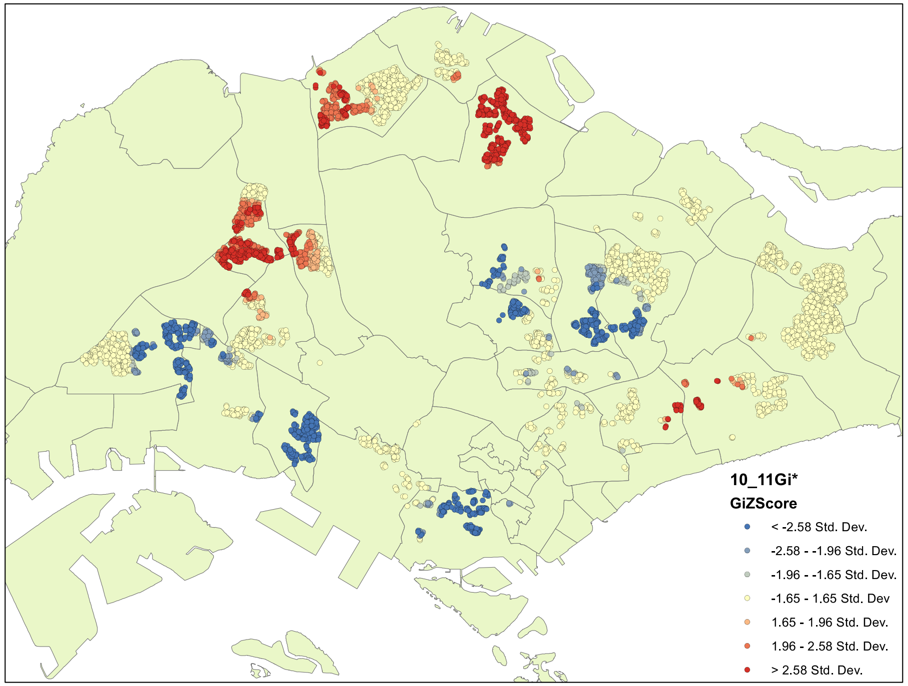
Note: The figure shows the distribution of average monthly electricity construction of HDB Block in Singapore for the sample periods 2009-2011. The Y-axis shows the frequency of households, and the X-axis show the electricity consumption in KWh/month per HDB blocks. Source: Data obtained from National Environmental Agency (NEA), 2013

Figure 3: Clustering of block-level changes in electricity consumption for HDB housing between 2009 and 2011

a) **Sub-period 2009-2010**

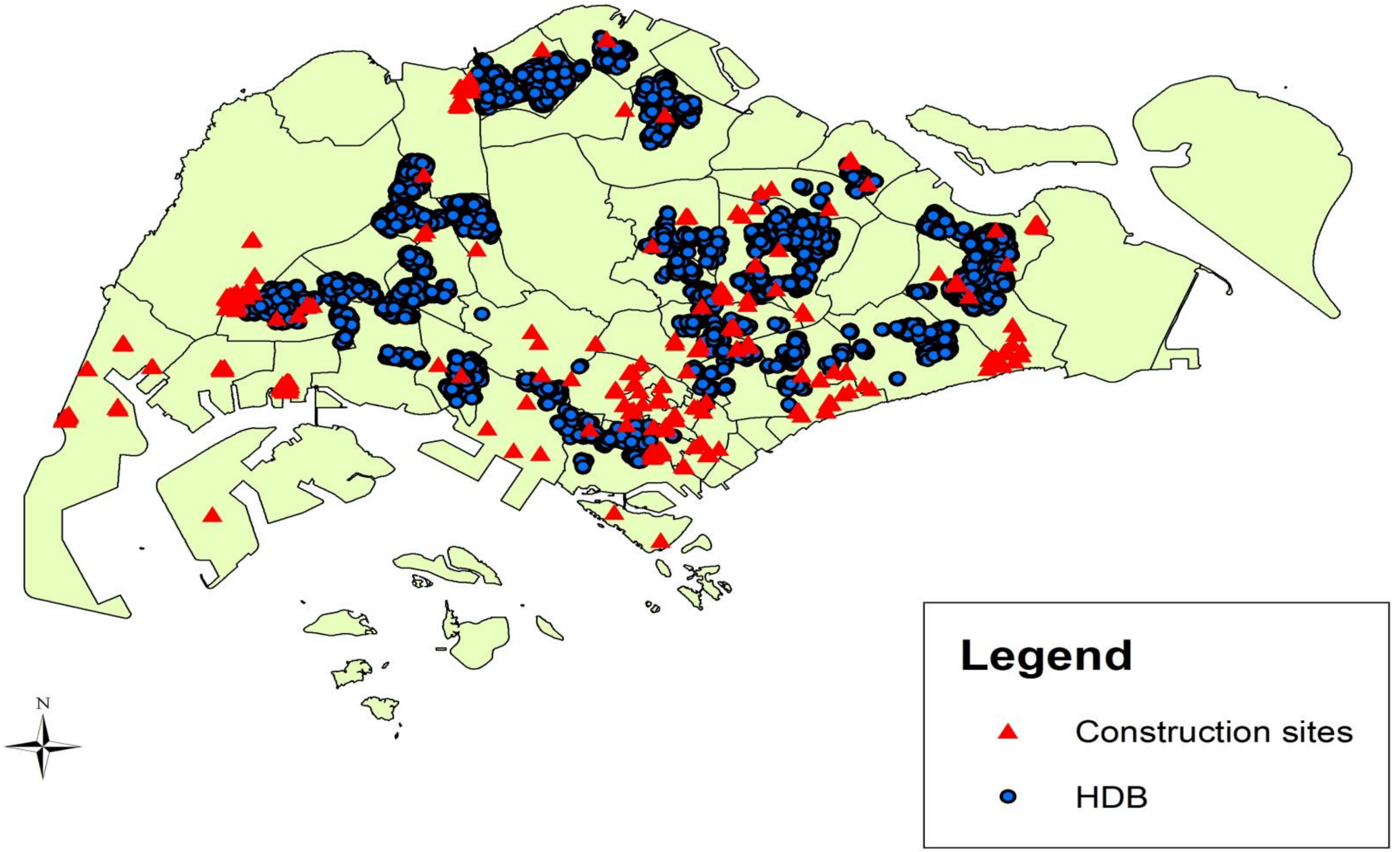


b) **Sub-period 2010-2011**



Note: The relative changes in block-level electricity consumption between 2009 and 2010 (left image) and between 2010 and 2011 (right image). The color gradient of blue to red represents the strength of clustering of low and high values respectively (as standard deviations), not necessarily the magnitude of those values. We can see that increases in consumption tend to be clustered in northern districts.

Figure 4: Map of Singapore showing location of construction activity in Singapore during 2009-2011



Note: The figure plots the location of construction sites (indicated by red triangles) and also sample HDB blocks for the periods 2009-2012. The electricity consumption data are obtained from the National Environmental Agency (NEA) and the construction data are obtained from the Building Construction Authority (BCA). We map the two sets of data on the GIS maps.