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Evaluation of the Public Sector Energy Efficiency Loan Scheme (Salix) in the UK

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ABSTRACT

This paper examines the impact of the Public Sector Energy Efficiency Loan Scheme, delivered by Salix Finance Ltd (Salix) on energy consumption of the institutions affected by this policy. The scheme provides interest-free loans to public sector organisations to support energy efficient installations, thereby reducing energy consumption, energy bills and greenhouse gas emissions. The scheme is available to Local Authorities, NHS / Foundation Trusts and emergency services, schools (including academies), Higher Education Institutions and Further Education Institutions.

This paper focuses on primary schools who have engaged with the scheme. We provide a quasi-experimental assessment of the projects funded by the scheme in the financial year 2013/14 with regard to electricity and gas consumption. Methodologically, we use a novel approach, the Synthetic Control Method (SCM) which is particularly useful in this instance, considering the lack of an obvious control group. In the SCM, the control group is built as part of the analysis, in order to replicate characteristics of interest in the treated group, i.e. the schools implementing projects funded by the scheme. It is also able to implement inference analysis without the need for large number of units in the treated and control group.

Our results suggest a reduction in electricity consumption in the schools for which data were available compared to schools not receiving for funding under the scheme. The impact on electricity appears more marked, perhaps a reflection of the higher number of projects for which data were available.

Keywords: energy consumption, treatment effect, synthetic control method

1. Introduction

The focus of this paper is to present the findings from the Quasi Experimental Analysis of the Public Sector Energy Efficiency Loan Scheme, delivered by Salix Finance Ltd (Salix). The scheme comprises interest-free loans provided to public sector institutions to implement energy efficient installations, aiming at reducing energy consumption and eventually greenhouse gas emissions and energy bills. Applications to the scheme can be made by a number of institutions, i.e. local authorities, NHS/foundation trusts, further and higher education institutions, and schools. We focus on lighting and insulation projects implemented in 2013/14 in primary schools, to examine the impact in electricity and gas consumption, respectively.

To empirically assess scheme implications, we implement the synthetic control methodology (SCM) introduced by Abadie and Gardeazabal (2003). The SCM is a relatively innovative quasi-experimental approach for building a counterfactual for policy evaluation. This methodology can be used when the parallel trend assumption required by the Difference-in-Difference approach is not met and when developing a comparison group is not straightforward. In the case of the SCM, and the effect of unobservable factors is not assumed to be constant across time, like in the case of the Difference-in-Difference, and implementation in small samples is feasible. This method also allows for the possibility that units are treated (in our case meaning the project funded by Salix is implemented) at different points in time. A synthetic control is built by using a weighted average of potential control units (i.e. using data from organisations not engaging in the scheme), greatly simplifying the process of forming a counterfactual. This control best reproduces the characteristics of the treated units (i.e. scheme participants) during the period before the treatment. After estimating the effect of the projects on electricity and gas consumption, placebo experiments are run to assess the statistical significance of the estimates. Results suggest that electricity and gas consumption decreased due to the implementation of lighting and insulation projects respectively, with the effect on electricity consumption being highly significant.

2. Empirical Methodology

The SCM is a relatively new approach to assess policy impact, developed by Abadie and Gardeazabal (2003) who examined conflict implications on growth. The method was further advanced by Abadie et al. (2010) to estimate the impact of a tobacco related law on cigarette consumption. A number of studies examining energy related issues have applied the SCM. Lee and Melstrom (2018) study the effect of a gas initiative on electricity imports, Munasib and Rickman (2015) examine the impact of shale gas boom on employment, per capita income and poverty rate of the affected states, and Rickman and Wang (2020) study the response of economic growth and employment to the cycle of US oil and gas extraction sector. Closer to the topic of our research, Lin and Hung (2016) examine the change in energy use due to initiatives of the Energy Service Company (ESCO) industry targeting energy efficiency and savings. The SCM method has also been adopted in micro-studies, e.g. with a focus on health related outcomes. Kreif et al. (2016) examine the effect of a health policy implemented in hospital on mortality rate, and Olsen (2018) considers the response of GP visits when a group of people become exempted from primary care co-payments.

For the aim of this paper, the SCM has several advantages compared to other more common regression-based approaches. In the case of this scheme, there are multiple treated units which implemented projects either in 2013 or 2014 and the number of identified treated units was relatively small. All these conditions can be well addressed by SCM.

2.1 Methodology: Non-technical

A number of steps are involved in the implementation of the SCM:

1. Identify the donor pool. The donor pool contains units which can be used to synthesise the control unit using ‘characteristics’ observed in the treated and potential control units (e.g. whether the building is located in an urban or rural area).
2. Variables are then identified to select which members in the donor pool should be used to synthesise the control unit, using variables affecting energy consumption (e.g. total floor area).
3. Control units are synthesised by replicating (as close as possible) the pre-treatment values of the variable of interest in the treated units. The variables used in the process of synthesising the control unit are selected on the basis of the Root Mean Square Prediction Error (RMSPE)[1].
4. Placebo tests are implemented in place of ordinary confidence intervals to assess the statistical significance of the estimates. In placebo tests, each member of the donor pool is taken in turn as a ‘pretend’ treated unit. The difference between the value of the outcome in the treated unit and its synthetic control, and between each placebo unit and its synthetic control is used to assess confidence in the analysis through the creation of pseudo p-values. These are generated by comparing the estimated savings in the treated unit to the distribution of savings obtained when pretending that each member of the pool was being treated.
5. A judgement on the confidence of the additionality of the estimates delivered by the SCM can be formed through the placebo analysis. A large pseudo p-value suggests that the estimated impact could be due to chance. Measures which might have been funded regardless of the scheme are likely to produce relatively high pseudo p-values. On the other hand, additional measures funded by the scheme are expected to display relatively low pseudo p-values.

The SCM is considered an appropriate methodology for the quasi-experimental evaluation of the scheme as its implementation is not impaired by the consequent small size of viable groupings of ‘projects’. Another advantage of the SCM is that this approach does not require the existence of control units, as they are created (synthetized) by recombining information from units not affected by the policy.

2.2 Methodology: Technical

Following Abadie et al. (2010), the treatment effect can be expressed as follow:

$$\alpha_{it} = Y_{it}^{I} - Y_{it}^{N} \tag{1}$$

where α_{it} is the treatment effect for unit i at time period t, Y_{it}^{I} is the observed outcome for the treated unit and Y_{it}^{N} is the counterfactual, i.e. what would have happened if the unit was not under treatment. The outcome variable Y is electricity or gas consumption. We have $t = 1, \dots T$ time periods with T_0 $(1 \leq T_0 \leq T)$ being the treatment period. The unobserved outcome Y_{it}^{N} is given by:

$$Y_{it}^{N} = X_i\theta_t + \lambda_t\mu_i + \varepsilon_{it} \tag{2}$$

where X_i is a vector of covariates, θ_t is a vector of parameters, λ_t stands for unobserved common effects, μ_i are unit specific unobserved effects and ε_{it} are zero mean errors. The units of interest are primary schools and the vector of covariates includes annual electrical or thermal fuel usage, operational ratings, total floor area,

[1] Generally speaking, the root mean square error reflects the difference between two data points; it is used in regression analysis to measure the distance between the fitted line and the data points. In the SCM, the synthetic control unit is composed using weights attributed to control units, such that to minimise the difference in the predictors during the pre-treatment period between the treated and a weighted average control unit. These weights minimize this distance, targeting the lowest root mean square prediction error. In this way, the synthetic control unit matches as close as possible the pattern of the treated unit in the pre-treatment period.

the presence or not of air-conditioning, school capacity, whether the school is located in urban or rural area, whether it has a nursery, and a number of lagged outcome values to achieve a better match of the constructed control unit to the treated one in the pre-treatment period.

Let $\boldsymbol{w}$ being a vector of weights $(J \times 1)$ such that $w_j \geqslant 0 \; for \; j = 2, \dots J$ and $w_2 + \cdots + w_j = 1$. If w_j^* exists such that,

$$\sum_{j=2}^{J} w_j^* Y_{it} = Y_{1i}^{I} \; for \; t = 1 \dots T_0 \;\; \text{and} \qquad (3)$$
$$\sum_{j=2}^{J} w_j^* X_i = X_1,$$

this means that there is a set of w_j^*used to compute a weighted average of schools, i.e. the synthetic control school, from the donor pool . This synthetic control best matches the treated units in the pre-treatment period. Expression (3) cannot hold exactly. The degree of deviation will define how well the synthetic control unit has been matched to the treated one. The treatment effect can be estimated as follow:

$$\widehat{\alpha_{1t}} = Y_{1t}^{I} - \sum_{j=2}^{J} w_j^* Y_{it} \qquad (4)$$

The vector $\boldsymbol{w}^*$is chosen such that to minimize the distance $\|Z_1 - Z_0 w\|$, where Z_1 is the vector of pre-treatment features of the treated school and Z_0 is the vector of pre-treatment features of the non-treated schools. The synthetic control school is generated by optimally choosing the weights to minimize the distance between these two vectors. According to Abadie et al. (2010), $\boldsymbol{w}$ is chosen to minimize $\sqrt{(Z_1 - Z_0\boldsymbol{w})'\boldsymbol{V}(Z_1 - Z_o\boldsymbol{w})}$ where $\boldsymbol{V}$ is a positive definite, diagonal matrix which minimizes the mean squared prediction error (MSPE) in the period before the treatment.

3. Data and matching process

Different databases were used to build the sample used in the analysis. The analysis covers the period from 2004 to 2015, and the projects are implemented in financial year 2013/14. This implies that we can observe three years of treatment, if treated in 2013, or two years of treatment for projects implemented in 2014. Focusing on the average treatment effect, we run a panel analysis which can allow for the implementation year to differ across schools. The impact can be separately estimated for each year of implementation. Due to the panel dimension, we estimate the impact of the scheme for the years in which treatment overlaps across schools, therefore for 2014 and 2015. The meter consumption database held by the Department of Business, Energy and Industrial Strategy (BEIS) was matched to data from the Department of Education and the Display Energy Certificates (DECs) in order to develop a dataset which combines electricity and gas consumption with characteristics of the schools and of the school building.

Annual meter reading data were assessed to ensure they related to the fuel type affected by the project (i.e. if a school implemented a lighting project, data were required for the school's electricity meter) and that the quality of the data was sufficient for use in the impact assessment. Checks were made by visualising data in order to identify (a) step change patterns, (b) V-spike patterns, (c) inverted V-spike patterns, or (d) a combination of V-spike and inverted V-spike patterns occurring before the project was implemented. Step-change patterns were deemed plausible if they occurred once, on the basis that this may indicate a change in the characteristics of the school, i.e. adding floor area. Organisations having more than one step change in the data, however, were discarded as frequent step-changes may indicate issues with the data, rather than changes in the organisation. V-spike patterns were deemed implausible if one-year decreases in consumption were higher than 33% of the consumption in the previous year. Equally, an inverted V-spike was deemed implausible if one-year increases in consumption were higher than 33% of the consumption in the previous year. In both cases, data were interpolated for the year in which consumption dropped or increased significantly. Some data showed an inverted V-spike occurring after a V-spike, likely indicating estimated and corrected readings. As this required correcting data for two consecutive years, these organisations were removed rather than interpolated, as it was not always clear which amount of consumption had been wrongly assigned to which specific year.

More specifically about the data related to the schools' characteristics, variables describing the building where energy is consumed, like annual electrical and thermal fuel usage, operational ratings, total floor area and info about air-conditioning are sourced in the DECs. In addition, further features like school capacity, whether the school belongs to an urban or rural area, and whether it has a nursery are obtained from the Department of Education schools' database.

4. Results

The analysis explores the changes in energy consumption attributed to the implementation of energy efficient projects, by comparing the differences between schools implementing projects funded by the scheme and the synthesised control units. Negative values indicate a reduction in energy consumption compared to what would have happened if the project had not been implemented and positive values indicating an increase in energy consumption. The findings of this analysis can be found in the "Public Sector Energy Efficiency Loan scheme: interim evaluation report" (BEIS, July 2018).

Energy consumption in 2013, 2014 and 2015 was explored. As projects were funded in financial year 2013/14, the calendar year of the treatment is not known with certainty. In most cases, analysis is based on the assumption that any impact of the project(s) is observed in 2014 and 2015. However, in those cases where a non-negligible change in the pattern of consumption was observed in 2013, the impact of the policy is considered also for 2013.

We first focus on the impact of lighting projects on electricity consumption. Lighting projects are the most common type of projects implemented in participating maintained primary schools. Energy consumption data were analysed for 18 projects implemented in 2013-14 (based on data availability since 2004 to 2015).

The results show evidence of a significant impact of lighting projects on electricity consumption in participating schools compared to non-participants in the scheme. The average impact of lighting projects implemented in primary schools in 2013/14, estimated through a panel analysis (i.e. analysis across all projects), shows a reduction in electricity consumption of about 12% in the first year after implementation of the project and about 21% in the second year after implementation. In both cases the impact is statistically significant at 1% level of significance, therefore showing strong confidence in the estimated results. Table 1 provides the estimated average treatment effect for the first and second years of implementation. Figure 1 is a graphical exposition of the average treatment effect. The figure shows the anticipated trajectory for electricity consumption (the synthetic control line). The actual trajectory for treated units is substantially different after the vertical line (i.e. the last year of the pre-implementation period). This is another way in which the analysis can be used to express the additional impact of the scheme.

Table 2. Impact of the scheme on electricity consumption in primary schools implementing lighting projects with associated p-values.

	First year of implementation (2014)	Second year of implementation (2015)
Estimated impact (KWh)	-9,606	-16,763
Impact (%)	-11.8%	-20.6%
p-value	.00***	.00***

Figure 2. Electricity consumption in the average treated unit and related synthetic control

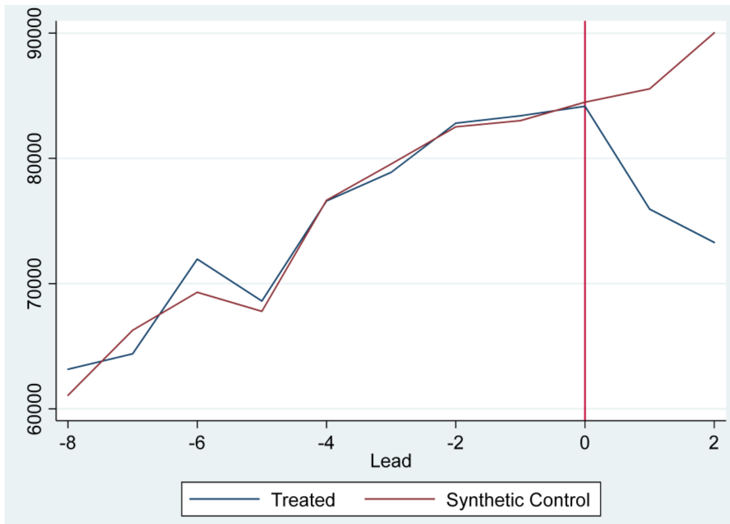

Figure note. KWh in y-axis. Years are represented in the x-axis, with the vertical line at 0 reflecting the last year of the pre-implementation period.

We now consider the effect of insulation projects on gas consumption. Insulation projects are the most common type of projects affecting consumption of natural gas in participating maintained primary schools. Gas consumption data were analysed for 6 projects implemented in 2013-14, for which they were available data from 2004 to 2015. The average impact of insulation projects implemented in primary schools in 2013/14 estimated through a panel analysis (Table 3) shows a decrease in gas consumption of 6.4% in the first year after the project was implemented (with a low p-value but close to significance only at the level of 10%) and an increase in gas consumption in the second year after the implementation (1.7%) which is however highly non-significant. The panel analysis exhibits a graphical representation of the average treatment effect in Figure 3. The figure shows that the actual trajectory for treated units is comparable after the vertical red line (i.e. the year when the project is implemented) to the anticipated trajectory for gas consumption (the synthetic control line), with the first year of implementation showing a decrease in gas consumption which is not statistically significant at the usual levels of significance. Lack of significance can be due to the limited set of treated schools. Statistical significance might have been obtained if a larger sample of treated units has been available.

Table 4. Impact of the scheme on gas consumption in primary schools implementing insulation projects with associated p-values.

	First year of implementation (2014)	Second year of implementation (2015)
Estimated impact (KWh)	-20,952	5,592
Impact (%)	-6.4%	1.7%
p-value	0.15	0.9

Figure 4. Gas consumption in the average treated unit and related synthetic control

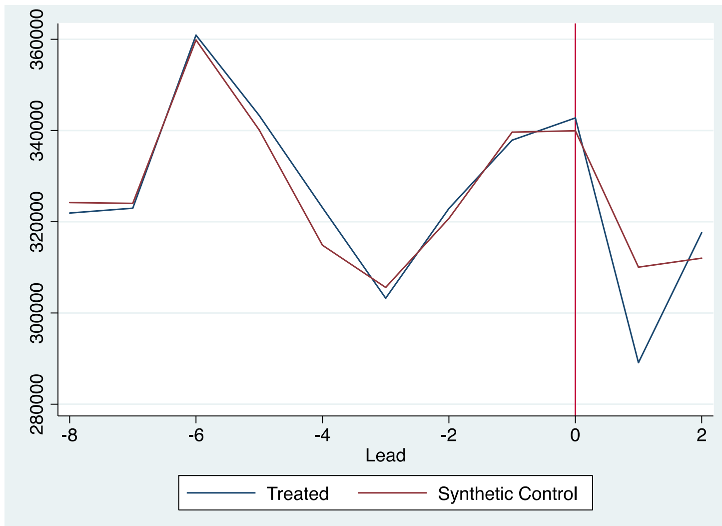

Figure note. KWh in y-axis. Years are represented in the x-axis, with the vertical line at 0 reflecting the last year of the pre-implementation period.

5. Conclusion

This paper presented the outcomes of the impact assessment of the Public-Sector Energy Efficiency Loan Scheme (Salix) on energy consumption of primary schools. In particular, we estimated the effect on electricity and gas consumption of lighting and insulation projects implemented in 2013/14. We used the Synthetic Control Method (SCM) and data from 2004 to 2015. This quasi-experimental evaluation methodology is particularly suited for evaluation with relatively small sample and when it is difficult to identify a targeted control group. The SCM forms a control group using a weighted average of non-treated schools which reflects the characteristics of the treated unit as close as possible before the implementation of the policy.

The results suggested that lighting projects implemented by participating schools caused a decrease in electricity consumption as compared to non-participating schools. This impact was found to be highly significant in both years of policy implementation, with an estimated decrease of about 12% and 21% in the first and second year, respectively. Gas consumption was found to decrease by 6.4% in the first year of implementation for schools adopting insulation projects, compared to non-participants. Although the estimated impact did not appear to be significant (p-value of 15%), significance could have been possibly achieved with a bigger sample of treated units.

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