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Abstract

This paper conducts a meta-analysis of 32 electricity demand response programs in the residential sector to understand whether their success is dependent on specific characteristics. The paper analyzes several regression models using various combinations of variables that capture the designs of the programs and the socio-economic conditions in which the programs are implemented. The analysis reveals that demand response programs are more likely to succeed in highly urbanized areas, in areas where economic growth rates are high, and in areas where the renewable energy policy is favorable. These findings provide useful guidance in determining where and how to implement future demand response programs.

Keywords: residential electricity; demand response; meta-analysis; demand side management[1]

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[1] Abbreviations: CPP/CPR (critical peak pricing/rebates), DR (demand response), GDP (gross domestic product), OLS (ordinary least squares), RE (renewable energy), ROC (receiver operating characteristics), RTP (real time pricing), TOU (time of use)

1. Introduction

The share of renewable sources in electricity generation is increasing significantly, particularly in Europe [1]. This increasing share tends to increase the variability of overall electricity supply. Non-intermittent capacity can be used to fill the valleys in such generation, but is a costly solution since backup power plants will only be used for limited periods of time. Further, although storage technologies are improving, they are still expensive and inefficient at present [2].

A more viable option is to adjust the demand for electricity, through demand response (DR) programs, which aim to modify the demand patterns for electricity by encouraging its use during peak generation and discouraging its use at times when the load on the grid is highest. One means of modifying demand is through the use of time-varying pricing, which broadly comes in three forms: time-of-use pricing (TOU) varies prices over the hours of the day with higher prices during peak periods, critical peak pricing/rebates (CPP/CPR) increases prices or provides rebates for conservation during the critical peak hours, and real time prices (RTP) allow prices to vary dynamically with the marginal cost of electricity [3]. Other means of modifying demand may involve the use of external load control techniques.

DR policies had been slow to emerge across Europe due to limited knowledge on the energy saving capacities of DR programs and the high costs for associated technologies and infrastructures [4]. However, DR is now seen as a promising option for the integration of renewable energy (RE) [5]. The European Commission (EC) estimates the potential response by 2030 at 160 gigawatts (GW), against current programs that achieve about 20GW [6]. The Commission's recent "Clean Energy for All Europeans" proposal further proposes that customers should be entitled to access dynamic pricing contracts, DR programs, smart metering systems, and better information on their consumption [7].

Consequently, DR is being promoted through enabling policy frameworks in countries such as France, Belgium, Finland, and the UK – though several countries still face significant regulatory barriers or do not yet view demand flexibility as a resource – and DR programs are being increasingly tested and implemented, including in the residential sector[2] [6].

Residential DR programs can however be challenging to implement successfully due to the limited price responsiveness of households, equity considerations, and the high costs of metering infrastructure [10]. A further consideration of households' price – and overall – responsiveness is the focus of this paper.

There have been a number of studies aimed at better understanding household responsiveness to demand side management.

But this existing research has been fragmentary, due to a varying focus on different aspects of DR programs. Faruqui and George [11] found that responsiveness varies with rate type, climate zone, season, and air conditioning ownership. Brent et al [12] state that price changes lead to greater conservation effects than moral and social arguments, that knowledge of consumption can maximize the effectiveness of time-varying pricing, and that enabling technology increases the effectiveness of such pricing. The

[2] An overview of European smart grid projects is available with the EC's Joint Research Center [8], while a list of demonstration projects supported by the US government is available at the US Department of Energy [9].

consumer behavior studies under the US government's Smart Grid Investment Grant program found that enrolment under opt-out approaches was higher than under opt-in approaches due to status-quo effects, loss aversion resulted in higher retention rates for CPR than for CPP, and higher price ratios led to greater response [13]. Kessels et al [14] conclude that dynamic pricing schemes should be simple to understand, with timely notifications of price changes, a considerable potential effect on the energy bill, and automated control. Often the success of the pricing scheme depends on factors influencing the behavior of end users. Gyamfi et al [10] therefore suggest greater use of economic behavior-based approaches to overcome some of the challenges to achieving effective voluntary demand reductions.

Existing research has also occasionally thrown up conflicting findings. For instance, Gyamfi et al [10] found that a high fraction of households – particularly the richer ones – did not respond to price signals. However, the Irish Commission for Energy Regulation [15] found that ToU tariffs do reduce electricity usage, and that higher-consuming households tended to deliver greater reductions. Muratori et al [16] found that shifting consumption may lead to steeper rebound peaks, while Cosmo and O'Hora [17] found that reductions lasted beyond the peak period and that post-peak spikes in usage were not observed.

Further, Flaim et al [18] claim that the prevalence of dynamic pricing programs remains limited on account of too little synthesis of existing research and an over-reliance on simple yet misleading performance metrics. Most attempts to aggregate research on DR programs have taken qualitative approaches, and have mainly focused on the characteristics of the program, such as pricing structures or the existence of load controls. For instance, Kessels et al [14] frame results from existing meta-reviews as four hypotheses on user response and test these hypotheses using a case-based approach. Stromback et al's [19] review of feedback and pricing pilots offers findings similar to Brent et al [12], based on basic statistical analyses such as proportions and weighted averages. Hobman et al [20] use insights from psychology and behavioral studies to draw lessons on DR design. Faruqui and Sergici [21] contain their analysis of 34 studies to the impacts of price ratios and enabling technologies. Faruqui et al [22] further review a dozen pilot studies only for the role played by information feedback.

There is a need for more rigorous analysis of the DR experiences, collecting a range of DR aspects under one study, and taking into account other socio-economic determinants, in order to obtain more broadly valid findings. This paper attempts to address these needs, by undertaking a meta-analysis of existing literature on DR programs. It uses a logistic regression approach in aggregating results from various studies to distil common findings and trends. The paper goes beyond considering characteristics of DR programs to also look at the relationships that socio-economic environments may have with the success of these programs. This approach helps explain whether any socio-economic factors are correlated with, or contribute to, the chances of a successful DR implementation. In this way, it complements the findings of studies such as Kessels et al [14].

2. Methods

A meta-analysis statistically combines evidence from multiple studies with an aim to identify either common effects or common causes for variation on specific research questions; it is often beneficial for overcoming the subjectivity of narrative reviews, as explained in [23] and [24]. Meta-analyses have typically been used in the field of medicine [25] [26], although their use in energy economics is not yet widespread.

In the field of energy, Sundt and Rehdanz [27] use a meta-analysis to understand consumer preferences for a greater share of RE in their electricity mix. Mattmann et al [28] offer a meta-analysis of 32 studies on the non-market valuations of wind power externalities. Van Der Kroon et al [29] conduct a meta-analysis to understand household fuel choice and fuel switching behavior in developing countries and aim to contribute to energy transition policies.

2.1 Data gathering and categorization

To undertake the present analysis, this paper drew upon articles from journal databases, and complemented this with studies from sources that covered analyses of DR initiatives, as well as with more general searches for other unpublished DR initiatives in an effort to address publication bias.

The focus of the search was on time-varying DR measures; studies looking at tiered pricing or at general determinants of electricity consumption behavior were excluded from the analysis. Data gathering thus used combinations of search terms such as but not limited to “residential,” “demand response,” and “electricity.”

Studies published before 2006 were not considered, in an effort to stay relevant with the current state of play, although the underlying projects covered in these studies may have been deployed earlier.

Based on these criteria, the final sample included 32 studies, which are listed in Appendix A. Two of these are from emerging markets – China [30] and South Africa [31] – while the rest are from Europe and the US, reflecting the prevalence of such programs in developed countries. No results were found in low-income developing countries, since DR programs have either not been rolled out in such countries or are too recent to be able to yield concrete results.

The dependent variable is the success or failure of the DR programs, and it was coded in binary form (successful = 1, unsuccessful = 0). The 32 papers included in the meta-analysis looked at DR programs from three broad perspectives, and the dependent variable was determined based on the perspectives as follows: (i) If the study took the perspective of the electricity provider: The program was a success if the author of the study concluded that peak load was shifted and the shift was statistically significant; (ii) If the study took the perspective of the electricity consumer: The program was a success if the author of the study concluded that financial savings from load shifting were statistically significant; and (iii) If the study took the perspective of a potential rollout: The program would be a success if the author of the study concluded that the survey respondents were willing to accept the implementation of a DR program.

In this way, the definitions of the DR programs as successful/not successful were based on the conclusions of the underlying studies. The authors of this paper do not attempt to impose a standardized definition of success across the heterogeneous range of underlying studies.

A few studies included multiple DR measures or multiple offerings of a DR measure – Fell et al [32], for instance, studied the acceptability of five types of tariffs – or disaggregated their results – such as Bartusch and Alvehag [33], who studied DR based on type of housing. In such cases, the analysis focused on aggregated results where possible, and otherwise focused on those measures/levels that had the most complete information available for each of the independent variables.

The explanatory variables are broadly grouped under two categories: those that describe the structures of the DR programs (intrinsic variables), and those that describe the socio-economic conditions under which the programs were implemented (extrinsic variables).

Data on the intrinsic features of the DR programs was obtained from the underlying studies themselves. The intrinsic variables are listed in table 1 below.

Table 1: Intrinsic explanatory variables

Number	**Variable**	**Unit of Measure**
1	Price change	*Binary (Yes/No)*
2	Type of time-varying pricing	*Binary (Static/Dynamic RTP)*
3	Peak-to-off peak price ratio	*Numerical (Ratio of prices)*
4	Automated load controls	*Binary (Yes/No)*
5	Voluntary enrolment in program	*Binary (Yes/No)*
6	Time since program rollout	*Numerical (Months)*
7	Duration of study	*Numerical (Months)*
8	Off-peak hours per day	*Numerical (Hours)*

It may be noted that the peak to off-peak ratio in variable 3 was estimated at the lowest levels at which the study was successful or the highest levels at which it was unsuccessful. Exceptions were made for RTP, where range bounds were used, and for CPP.

The second set, of extrinsic variables, are relevant to the levels of electricity consumption and/or response flexibility, and it is thus expected that they would also play a role in influencing the success of DR programs. Other socio-economic indicators that were not covered in existing literature are not included in this analysis.[3]

This data was sourced through multiple datasets, including those of the World Bank Group, World Weather Online, and the REN21 network. To enable comparability of the data, per capita GDP figures were converted into US dollars using the average exchange rates of the years for which the data was drawn. Further, in some instances data on indicators such as GDP per capita was available only for earlier years – data in these cases was extrapolated to 2015 using recent growth rates for the respective regions.

The authors obtained this data for the months and regions where the DR program was in operation, where such granular data was available. Where such data was not available, national-level and annualized data

[3] Although GNI might be considered a closer indicator to disposable income, since GDP data was more complete at a granular level than data on disposable income, and since there is a strong correlation (0.9998) between global GDP and GNI numbers [34], this analysis uses GDP per capita as an indicator of income

was drawn. Thus, based on the scope of the DR program and on availability, the levels of data vary within each variable. This data is tabulated in Appendix A.

The extrinsic variables are summarized in table 2, together with typical sources used for the data, as well as references to some respective literature that highlights the relevance of these variables.

Table 2: Extrinsic explanatory variables

<table>
<tr><th>Number</th><th>Variable</th><th>Unit of Measure</th><th>Sample data source</th><th>Studies linking variable to consumption flexibility</th></tr>
<tr><td>9</td><td>GDP per capita</td><td>Numerical (US$, 2015)</td><td>World Bank Indicators [35]</td><td>[11][42][43]</td></tr>
<tr><td>10</td><td>GDP growth rate</td><td>Percentage (2015)</td><td>World Bank Indicators [36]</td><td>[44]</td></tr>
<tr><td>11</td><td>Urbanization rate</td><td>Percentage (2015)</td><td>World Bank Indicators [37]</td><td>[45]</td></tr>
<tr><td>12</td><td>Average temperatures</td><td>Numerical (℃), during study periods</td><td>World Weather Online [38]</td><td>[11]</td></tr>
<tr><td>13</td><td>Electricity consumption</td><td>Numerical (kWh per capita, 2013)</td><td>World Bank Indicators [39]</td><td>[15][46]</td></tr>
<tr><td>14</td><td>Current shares of RE</td><td>Percentage (typically 2014)</td><td rowspan="2">REN21 [40]</td><td rowspan="2">[47][48]</td></tr>
<tr><td>15</td><td>Targets for RE</td><td>Percentage (variable years)</td></tr>
<tr><td>16</td><td>Tertiary education rates</td><td>Percentage (enrolment ratio, 2013)</td><td>World Bank Indicators [41]</td><td>[11][15][17]</td></tr>
<tr><td>17</td><td>RE policy</td><td>[{(15) – (14)}/{(Year (15) – Year (14)}]</td><td>-</td><td>-</td></tr>
<tr><td>18</td><td>RE Target / GDP growth</td><td>(15)/(10)</td><td>-</td><td>-</td></tr>
</table>

Variables 17 and 18 merit further explanation. The computed variable 17, ‘RE policy’ attempts to serve as a substitute for the levels of ambition of RE policies. It does so by dividing the difference between current RE shares and future RE targets by the number of years between the two, in order to obtain the required average annual increases in RE shares. Similarly, the computed variable 18, ‘Target/GDP growth’ is an interaction term that attempts to standardize RE targets against the economic growth rates of that region. It explores whether a DR program is more likely to be successful when the RE target is more ambitious relative to the economic growth. Aside from these, the analysis primarily focuses on main effects.

2.2 Boundaries of meta-analyses

Meta-analyses operate on the implicit assumption that the underlying studies are similar enough that they can be usefully combined and analyzed. However often they pool studies of varying quality, and suffer from publication bias. Meta-analyses that rely on ordinary least squared (OLS) regressions can suffer from factual and methodological heterogeneity, heteroscedasticity, multicollinearity, and autocorrelation. Nelson and Kennedy [49] examine the current state of meta-analyses in environmental economics and notes that among others heteroscedasticity is particularly likely to be a concern.

However, heteroscedasticity is not of concern in logistic regressions – an approach chosen here because it avoids the pitfalls of traditional meta-analyses – that have a binary-form dependent variable, where the residuals are distributed between only two points when plotted against the fitted values of the model. Therefore this analysis does not include tests to check for the presence of this condition.

2.3 Regression equation

The model used in this paper takes the form

$$Ln[\pi(y)/\{1-\pi(y)\}] = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \varepsilon \ldots(1)$$

Where
Ln = natural logarithm
$\pi(y)$ = probability of event occurring
$\beta_0 \ldots \beta_n$ = regression coefficients
$x_1 \ldots x_n$ = intrinsic and/or extrinsic explanatory variables
ε = error term

This paper conducted several regressions using this equation. In all cases, the dependent variable was taken as the success of DR programs. However, each regression used different subsets of the intrinsic and extrinsic variables, creating different regression models, in order to test the relationships between the different variables. The authors did not attempt to conduct a regression – of the form outlined in equation (1) – that would include all the explanatory variables together, since the sample size was limited. Any one regression model included between two and five of the variables listed in tables 1 and 2 above, in such a way that each variable was considered for multiple regression models. Thus, the research was exploratory rather than confirmatory, and it consciously attempted to avoid a potential over-fit of the model.

In the regression models, the samples were also weighted in turn by the natural logarithms of the sample sizes and by the GDP per capita of the respective regions, in addition to the non-weighted regressions, to determine whether such weighting would affect the results.

3. Results

3.1 Identifying a base model

The analysis conducted regressions with different combinations of intrinsic and extrinsic variables, and the variables in a number of models were found to be statistically significant. To illustrate, the results from two such models, where the variables are weighted by the natural log of the sample sizes, are summarized in table 3.

Table 3: Results of Select Models with Intrinsic Variables

	Variables	**Sample size**	**Sig.**	e^{β}	**R Square**	**Correctly predicted values**	**Area under ROC**	**Hosmer and Lemeshow Test** *Chi square*	*Significance*
Model 1	Voluntary enrolment Duration of study	24	0.281 0.037	1.811 1.034	0.074	77.8%	0.632	58.726	0.000

Model 2	Auto load control Urbanization rate Tertiary education rates	29	0.000 0.004 0.220	0.136 1.031 0.144	0.183	81.8%	0.633	48.910	0.000

The significance of the maximum likelihood estimates of the regression coefficients is determined using the Wald test. (e^{β}) denotes the effect of the variable on the odds ratio i.e. the odds of success increase multiplicatively by (e^{β}) per unit increase in the explanatory variable. Thus, for every 1% increase in the duration of a DR program, the odds of success of the program increase by 3.4% in model 1.

The table also summarizes the results of goodness-of-fit tests on the model, including the R Square values. This analysis uses the Nagelkerke R Square instead of the Cox & Snell R square, because the latter has an upper bound of less than 1 and so holds less intuitive appeal. Both models have low values under this R Square, suggesting a poor fit.

However, R Square values assess only comparative – not actual – goodness-of-fit, and lower R Square values tend to be the norm in logistic regression [50]. Thus the analysis also includes a comparison of observed to predicted values from the fitted models, as well as the areas under their receiver operating characteristic (ROC) curves. ROC curves are graphical plots of the true positive rates against the false positive rates, and the area under these curves is a good estimate of the strength of the model. As seen from Table 2, although the models are fairly successful at correctly predicting the outcomes, the areas under the ROC curves of the two models are not very high.

A final approach for determining the goodness of fit is through the Hosmer-Lemeshow statistics, which examine whether the observed proportions of events are similar to the predicted probabilities of occurrence using a Pearson chi square test. Significant test results, i.e. those with p-values below 0.05 indicate that the model is not a good fit. Though this test should be used with caution [51], the results of these tests are included here and demonstrate very low p-values.

Thus it is seen that while the models are found to be significant, their R Square values, Hosmer-Lemeshow test results, and areas under their ROC curves suggest that they are not good fits. Moreover, the intrinsic variables had several missing values, leading to smaller sample sizes and less robust models when these variables were included.

As a result, the analysis disregarded such models, and determined a model with the following combination of variables as being significant, as well as the best fit in forecasting success of the DR program: (i) urbanization; (ii) RE target; (iii) RE policy; (iv) GDP growth rate; and (v) RE target/GDP growth rate. This model was weighted by the natural log of the sample sizes. The stepwise regressions saw the intrinsic variables being removed from the model as they were not significant.

Table 4 demonstrates the regression coefficients and the statistical significance of the explanatory variables in the model. As seen, all the variables are significant at the 95% level. For every 1% increase in the targeted share of RE, the odds of success of a DR program decrease by 13.3%. Increases in the other explanatory variables increase the odds of success.

Table 4: Regression Coefficients and Statistical Significance of Variables in Equation

Variable	β	S.E.	Sig	e^{β}	Marginal impact on OR
GDP Growth Rate	2.508	0.824	0.002	12.278	1127.8%
Urbanization rate	0.064	0.025	0.011	1.066	+6.6%
Targets for RE	-0.142	0.039	0.000	0.867	-13.3%
RE Policy	0.827	0.351	0.019	2.286	+128.6%
RE Target / GDP Growth Rate	0.239	0.078	0.002	1.270	27.0%

This paper thus proposes the following model for consideration:

$$\text{Ln}[\pi(\text{success})/\{1-\pi(\text{success})\}] = -10.013 + 2.508(\text{GDP growth rate}) + 0.064(\text{Urbanization}) - 0.142(\text{target for RE}) + 0.827(\text{RE policy}) + 0.239(\text{RE target / GDP growth rate}) \quad \ldots(2)$$

Table 5 summarizes the results of some tests for goodness of fit on the model. The regression analysis for this model yielded a Nagelkerke R Square value of 0.447. This suggests that the model explains nearly 45% of the variation in the dependent variable, a significant improvement over the models in table 3. A comparison of observed to predicted values from the fitted model demonstrates that this model correctly predicts the success of the DR program in 81% of the cases. A likelihood ratio test, used to compare goodness of fit against a base model with no explanatory variables, yields a Chi-square value of 64.741 with 5 degrees of freedom, which is significant at the 99% level.

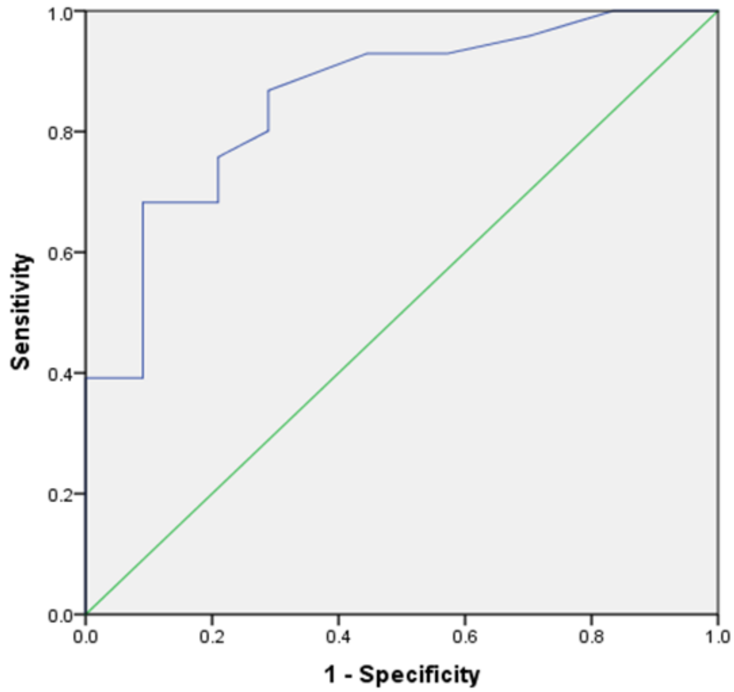
Table 5: Model Fit and Explanatory Power

Indicator	Value
R Square (Nagelkerke)	0.447
Correctly predicted values	80.90%
Likelihood ratio test P-value (Chi-square = 64.741 with 5 df)	~0.000

One limitation of this model is the presence of some correlations among the explanatory variables. In particular, as expected, correlations are noted between ‘RE Target,’ ‘GDP growth,’ and ‘RE Target/GDP growth.’ However, the variance inflation factors (VIFs) of these variables all lie between 1.2 and 4.1, suggesting that multicollinearity is not a problem. Further, removing any of these variables reduces the explanatory power of the model and does not greatly affect the remaining model coefficients. Thus it is preferable to retain them.

The ROC curve is seen in figure 1. In the figure, sensitivity (also called the true positive rate) measures the proportion of positives that are correctly identified as such. Specificity (the true negative rate) measures the proportion of negatives that are correctly identified as such, i.e. the percentage of unsuccessful DR programs that are correctly identified as not being successful. The area under this ROC curve is much higher than the initial models in Table 2, at 0.855.

Figure 1: ROC Curve for Base Model



3.2 Robustness against alternatives

A common practice is to compare the main model to close alternatives to examine how the main estimates of the regression coefficients behave when the regression model is modified. If the coefficients are not found to change significantly, they are determined to be robust and can be interpreted as the true causal effects of the associated explanatory variables. This plausibility and robustness is a good estimate of the structural validity of a regression model [52].

The current analysis therefore assesses the base model outlined above against several alternatives with different combinations of explanatory variables. In this paper, the base model is compared against the best three alternatives, chosen based on their overall significance and R Square. The results are summarized in table 6 below.

Table 6: Comparing Models

Model (variables)*	**Chi-square values**	**R square**	**Correctly Predicted Values**	**Correlations above 0.5**	**Variables with (e^{β}) > 1.1 or with (e^{β}) < 0.9**	**Area under ROC curve**	**Hosmer and Lemeshow values**	
							Chi sq.	*Sig*
Base (11, 15, 17, 18, 10)	64.741	0.447	80.9	3	4	0.855	17.002	0.030
Alternative 1 (9, 15, 17, 18)	34.760	0.260	80.9	1	1	0.765	31.878	0.000
Alternative 2 (11, 15, 18, 10)	58.315	0.409	83.9	5	3	0.821	24.998	0.002
Alternative 3 (11, 15, 17)	30.678	0.232	80.0	0	1	0.708	33.269	0.000

* Variables are denoted by their corresponding numbering from table 1

Thus, it is seen that the base model has the highest R Square, the second highest proportion of correctly predicted values, and the most number of variables with meaningful odds ratios, without having too many correlations among explanatory variables.

The Hosmer-Lemeshow test results for the different models are also included. While even the base model is not determined to be a very good fit, since it does well on the other indicators in table 6 and is also shown to be a better fit than the alternatives under the Hosmer-Lemeshow statistics, this paper retains this model as the most relevant one for analysis and further discussion.

3.3 Caution in interpreting the results

It should be noted that the analysis suggests a correlation between the variables, but does not imply the existence of a causal relationship. The results provided above are conditional upon (i) a small sample size; (ii) missing information in the underlying studies; (iii) limited diversity in the features of the DR programs; and (iv) varying levels of granularity of the socio-economic variables.

Thus, there is a possibility that increasing the sample size and improving the underlying data may yield different results than those presented here. One way this study attempts to reduce these risks is by limiting the approach to relatively straightforward statistical analyses. Conversely, this paper also aims to highlight the need for improving data, by demonstrating that such a meta-analytical approach is feasible. Keeping these points in mind, the results in section 3 are offered at least indicatively, if not definitively.

4. Discussion

As noted in section 3, the authors found that a number of different models partially explained the chances of success of DR programs, in addition to the base model proposed. These alternative models used different combinations of explanatory variables, and arrived at different regression coefficients with varying levels of significance. Though intrinsic variables such as duration of the study and the presence of automated load controls did appear to play a part in determining the success of the DR programs, the key finding is that extrinsic variables such as RE targets and policy, GDP growth rates, and urbanization were consistently statistically significant. Thus, even if the results in Section 3 are offered indicatively, they can yield a number of insights.

First, a DR program is very likely to be successful where economic growth rates are higher. Studies have shown that infrastructure investment – including investment in energy infrastructure – leads to higher economic growth and, in some cases, that growth spurs investment [53][54][55]. It is thus possible that DR programs are more likely to be implemented, and consequently more likely to be successful, in regions with higher growth rates.

Second, a DR program is more likely to be successful in urban environments. There might be two reasons for this: (a) the higher densities of populations in urban areas may create economies of scale and reduce the costs of such programs; and (b) urban consumers might be slightly more aware of energy and environmental issues [56][57][58].

Third, a DR program is less likely to be successful where national RE targets are high. The authors are not certain of the reasons behind this, but it is also conversely more likely to be successful when a strong RE policy exists. This could be because a strong RE policy may signal governmental commitment towards promoting RE and energy security, and may be associated with strong incentives and/or mandates, either to utility companies to deploy such programs, or to consumers to adopt them.

Fourth, there is some inverse interaction between the national RE target and the GDP growth rates in determining the success of a DR program. While a relationship between the RE targets and GDP growth rates may make sense due to associated infrastructure requirements, the interaction term in this analysis may be more relevant for moderating the main effects.

Education and income were not found to be significant predictors of DR success, which goes against expectations. However, this might be due to the limited size of the sample, and their effects might be partly included in the role of urbanization in predicting the success of DR programs. The omission of average temperatures and per capita electricity consumption patterns might similarly be on account of limited information. Alternatively, it is possible that temperatures do not affect DR programs because their effects are not significant or are offset by other factors. For instance, even during extreme weather events, reductions in electricity demand are possible due to the consequently higher dynamic prices [59].

Lastly, it is noteworthy that the final model does not include any intrinsic variables. This is possibly because: (i) the intrinsic variables had many missing values, and their inclusion significantly reduced sample sizes; and (ii) the DR programs were reasonably homogenous in structure – for instance most didn’t include automated load controls and most included voluntary enrolment options – thereby reducing the robustness of the regression models.

It is expected that future analyses, with more extensive data, would yield significant and robust models that include a mix of both intrinsic and extrinsic variables.

These findings have implications for shaping policy. This analysis suggests that the likelihood of success of a DR program is not just dependent on its structure, but also related to the socio-economic conditions under which it is implemented. Further study could argue a case to optimally structure DR programs such that they are most likely to succeed in their individual socio-economic environments. Perhaps this is most important in the case of developing countries, which do not yet possess adequate electricity infrastructure and present an opportunity to leapfrog traditional electricity markets.

5. Conclusion

This paper conducted a meta-analysis, using a logistic regression approach, on 32 residential electricity demand response programs to analytically determine whether their likelihoods of success were correlated with the structures of and contexts surrounding the programs.

The analysis found that the success appears to be correlated with the extent of urbanization in the region where the DR program is implemented, the renewable energy policy and targets, and the annual economic growth rates. While the sample size is small and the data is limited by missing values, the study offers the following guidance to increase the effectiveness of future DR programs: (a) Deploy DR programs in urban areas, particularly in faster-growing cities that are likely to have greater infrastructure spending; (b) Complement DR and electricity policy with supportive renewable energy policies; and (c) Couple electricity policy with wider economic policies and urban development planning, in order to also place it within the context of broader sustainable urban development.

Future research may focus on addressing existing gaps by considering a wider set of DR programs for analysis; especially as such programs start to be implemented in developing countries. In particular, it would be useful to look at the impacts of levels of awareness on demand flexibility and how this might affect the design of the programs. Specific to developing countries and emerging markets, it would also be useful to consider the impacts of DR programs on broader welfare considerations and other rebound effects.

Appendix A – Demand Response Initiatives and Data on Select Variables

#	Study	Country	Success (Y=1, N=0)	Sample (treatment group)	GDP per capita	GDP growth rate	Urbanization rate	Electricity consumption	RE Share	Year	RE Target	Year	Education rate
1	Broberg and Persson [42]	Sweden	0	918	50273	4.1%	86%	13870	63.3	2014	62.9	2020	63.0%
2	Bartusch and Alvehag [33]	Sweden	1	95	29214	4.1%	86%	13870	63.3	2014	62.9	2020	63.0%
3	Torriti [60]	Italy	0	1446	34011	0.8%	26%	5159	33.4	2014	26.0	2020	63.0%
4	Kobus et al [61]	Netherlands	1	77	44433	2.0%	100%	6821	10.0	2014	37.0	2020	78.5%
5	D'hulst et al [62]	Belgium	0	186	36269	1.4%	98%	7967	13.4	2014	20.9	2020	72.0%
6	Stamminger and Anstett [63]	Germany	1	41	42994	1.7%	100%	7019	28.2	2014	80.0	2050	61.0%
7	Fell et al [32]	Britain	1	2002	43734	2.3%	83%	5407	7.0	2014	15.0	2020	57.0%
8	Bartusch et al [64]	Sweden	1	50	50273	4.1%	86%	13870	63.3	2014	62.9	2020	63.0%
9	Carroll et al [65]	Ireland	1	1964	51289	7.8%	63%	5702	22.7	2014	42.5	2020	73.0%
10	Schleich et al [66]	Austria	1	775	41772	0.9%	100%	8513	70.0	2014	70.6	2020	80.0%
11	Campillo et al [67]	Sweden	1	400	89989	4.1%	100%	13870	63.3	2014	62.9	2020	63.0%
12	Kato et al [68]	Japan	1	88	22558	0.5%	100%	7836	12.2	2014	23.0	2030	52.0%
13	He et al [30]	China	1	236	16526	6.9%	56%	3762	11.1	2014	20.0	2030	48.2%
14	George and Toyama [69]	USA	1	8609	48525	2.4%	100%	7187	24.4	2014	50.0	2030	89.0%
15	Faruqui et al [70]	Canada	1	112642	41849	1.1%	82%	15519	31.2	2014	50.0	2025	-
16	Becker [59]	USA	1	10847	59472	2.4%	82%	12033	11.5	2014	25.0	2025	89.0%
17	Herter [71]	USA	1	457	61924	2.4%	97%	7187	24.4	2014	50.0	2030	89.0%
18	Allcott [72]	USA	1	590	61236	2.4%	100%	12033	11.5	2014	25.0	2025	89.0%
19	Nilsson et al [73]	Sweden	0	33	36388	4.1%	100%	13870	63.3	2014	62.9	2020	67.0%
20	Thorsnes et al [74]	New Zealand	0	332	48447	3.4%	100%	9084	75.0	2013	90.0	2025	80.0%
21	Finn et al [75]	Ireland	1	1	51289	7.8%	63%	5702	22.7	2014	42.5	2020	73.0%
22	Faruqui and Sergici [76]	USA	1	878	60751	2.4%	100%	12129	17.1	2014	20.0	2022	89.0%
23	Ericson [77]	Norway	1	295	74735	1.6%	80%	23326	69.2	2014	67.5	2020	76.0%
24	Carmichael et al [78]	Britain	1	1119	56233	2.3%	100%	5407	7.0	2014	15.0	2020	57.0%
25	Wolak [79]	USA	1	857	77893	2.4%	100%	21275	12.0	2015	50.0	2032	89.0%

26	Ericson [80]	Norway	0	312	74735	1.6%	80%	23326	69.2	2014	67.5	2020	76.0%
27	Gans et al [81]	N. Ireland	1	34779	26070	2.3%	63%	4182	17.8	2014	-	-	57.0%
28	Gyamfi and Krumdieck [82]	New Zealand	1	63	48089	3.4%	100%	9084	75.0	2013	90.0	2025	80.0%
29	Woo et al [83]	Canada	1	1245	40541	1.1%	82%	15519	59.0	2014	93.0	2050	-
30	Thondhlana and Kua [31]	South Africa	1	73	2803	1.3%	100%	4326	0.0	2010	21.0	2030	20.0%
31	Hall et al [84]	Australia	0	53	51949	2.3%	100%	10134	14.6	2015	23.0	2020	87.0%
32	“Alpenergy – VPS Allgau” [85]	Germany	0	260	41219	1.7%	75%	7019	28.2	2014	80.0	2050	61.0%

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