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Advertising and investment spillovers in the diffusion of residential energy efficiency renovations

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Abstract: This paper examines the diffusion of energy efficiency retrofits across the national housing stock and specifically examines whether the level of applications for subsidy support is impacted by advertising, either online or through print and radio media, and whether there are spillover effects from prior investments in retrofits on new retrofit subsidy applications. While there are numerous drivers of household retrofitting activities, the focus here is specifically on advertising and spillover effects. The analysis employs a Bass growth model using a subsidy scheme administrative dataset from Ireland. The research finds that some but not all advertising related to a retrofit subsidy scheme increases the level of scheme applications and also that there are spillover effects from a niche retrofit scheme targeting communities (covering both private and community buildings) on private applications for energy efficiency subsidy support.

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1. Introduction

The residential sector is the EU's third largest energy consuming sector, accounting for 24.8% of final consumption (Eurostat, 2016). As space and water heating respectively comprise 67% and 14% of residential energy use (EC, 2011), improving the energy efficiency of households not only provides a significant opportunity to reduce a nation's carbon footprint, but also provides the opportunity for households to save money on their energy bills and improve the comfort of their homes.

Many governments operate subsidy schemes to incentivise retrofitting at the household level. This is an attractive means of driving investments in energy efficiency in residential buildings, as households also benefit from such investments. Examples of these incentives include France's *crédit d'impôt développement durable* (Sustainable Development Tax Credit) or Germany's *KfW-Effizienzhaus* financing scheme. In Ireland, the *Better Energy Homes* scheme provides approximately 35% of the costs of retrofitting for certain energy efficiency retrofit measures. This is delivered in the form of a cash rebate following the completion of works. This is supplemented by the *Better Energy Warmer Homes* scheme, which provides the full cost of specific retrofitting works for recipients of specific welfare supports. While the Better Energy Homes scheme has been successful in providing grant aid for over 200,000 homes in Ireland (SEAI, 2017), this represents less than 15% of residential properties. A "significant increase in retrofitting of homes and business is essential" to reduce energy consumption to desirable levels (EPA, 2016).

Many of the research papers on residential energy efficiency retrofits focus on home owner's priorities and factors influencing participation in retrofit schemes (e.g. Aravena et al. (2016); Gamtessa (2013); Hoicka et al. (2014); Nair et al. (2010)). Our focus here is narrower, we investigate (i) whether the level of grant applications is impacted by advertising, either online or through print and radio media, and (ii) whether there are spillover effects from prior investments in retrofits on new retrofit grant applications. At its simplest level the spillover effects could be whether one home owner's visible retrofit investment influences the home owner's neighbours to retrofit their homes. As our data is not geo-coded, we are unable to directly investigate spillover effects at that spatial resolution level, however, we do investigate spillover effects between two parallel retrofit schemes. Both in the case of advertising and grant scheme spillover effects we are essentially investigating whether the dissemination of information on the benefits of home energy efficiency retrofits increases the level of grant applications. We consider spillover effects and advertising together for two reasons. Though unrelated both have relevance to grant scheme administrators attempting to achieve high levels of energy efficiency across the housing stock. A better understanding will help in the design and promotion of energy efficiency grant schemes. Second, from a technical perspective considering either in isolation would potentially lead to omitted variable bias in the results.

Drawing from the technology diffusion literature we employ a well established model to examine the diffusion of retrofits across the housing stock. Specifically, we use a Bass growth model to estimate the effects of advertising and other grant schemes on applications for retrofit grant support under the Better Energy Homes (BEH) support scheme operated by the Sustainable Energy Authority of Ireland (SEAI). We find that some but not all advertising related to a retrofit grant scheme increases the level of scheme applications and also that there are spillover effects from a niche retrofit scheme targeting communities (covering both private and community buildings) on private applications under the larger Better Energy Homes scheme.

The next section of this paper provides an extensive review of the relevant literature. Section 3 discusses the econometric methods employed to identify advertising and spillover effects. Section 4 then describes the data used in the empirical application. This is followed by the presentation of results in section 5, while section 6 concludes.

2. Relevant Literature

We first consider the theoretical literature in the field of technology adoption and diffusion. This is followed by a discussion of the applied literature, comprising spatial analysis of adoption and diffusion, and the literature studying the drivers of retrofitting activities, which affect households differently but ultimately are introduced exogenously to the household, in particular, spillover effects, policy activities and advertising. Finally, we review the literature employing product growth models, which is the main focus of this research.

2.1. Theoretical literature

Theories of technology diffusion provide insights into how the adoption of retrofit works may spread throughout the housing stock. The trickle-down theory of diffusion, whereby the wealthy adopt expensive technologies at the initial stage of diffusion while the less well off begin to adopt as prices fall over time (McCracken, 1985), and the technology acceptance model of diffusion, whereby greater acceptance and greater usefulness incite further acceptance (Davis, 1989) both focus on diffusion following the entry of a good or service to a population. 'Crossing the Chasm' theory, describes technology as being diffused from societal group to societal group (Moore, 2009). As the retrofit measures available to households in this analysis involve the installation of established technologies through developed markets and are available to all societal groups, it is unlikely that these theories are relevant to this analysis.

The adoption of energy efficiency retrofit measures is more likely to be consistent with two classical theories, these being the Two-Step Flow of Communication theory and Rogers' Diffusion of Innovation theory. The Two-Step Flow of Communication theory hypothesises that information is communicated from mass media to those who are more aware of a certain topic which is of interest to them. These *opinion leaders* then both attempt to convince others of their opinion or may be actively sought out by others who value their knowledge (Lazarsfeld et al., 1968). This theory has evolved in the age of social media into a multi-step flow of communication, where the media influences *voices*, whose influence are spread via *amplifiers*, who repeat the message of voices throughout social networks (Hilbert et al., 2016).

Rogers' theory of innovation describes five stages of diffusion, in which adopters undergo a five-step process involving first knowledge of an innovation, persuasion, the decision to adopt, implementation of adoption and finally confirmation (Rogers, 1962, 2010). Households make adoption decisions during different stages of the diffusion process. Innovators are the first movers who are willing to take risks in adopting a technology. These are followed by early-adopters, who, consistent with the two-step approach, are opinion leaders and communicate centrally to those before and after them in the diffusion chain. These are followed by the 'early majority', 'late majority' and finally laggards, who are the last to adopt. Innovators, early adopters, and 'early majority' are more status-motivated in adopting innovations, while 'late majority' and laggards perceive status as less significant. Rogers (2010) provides a discussion of the drivers of the rate of adoption, including economic factors, incentives, compatibility, complexity, trialability and observability. In particular, Rogers (2010, p. 232) suggests that the "observability of an innovation, as perceived by members of a social system is positively related to its rate of adoption".

2.2. Spatial analysis

A variety of methods are used to study the spatial diffusion of technologies in households. A commonly used approach involves using the installed base of adoptions in a local area at the beginning of a period as a predictor of current adoptions in that period. For example, Bollinger and Gillingham (2010) utilise a hazard model of adoption, using the installed base as a dependent variable to examine the adoption of solar photovoltaic technology in California at both zip code- and street-level. Their results indicate that at the average installed base, one further installation increases the probability of adoption in that zip code by 3.25 percentage points, an effect which is found to be five times stronger at street-level (Bollinger and Gillingham, 2010). Similarly, Richter (2013) examines the uptake of solar photovoltaic technology in UK households finding that at the average installation rate of 0.07% of owner-occupied homes, one more installation increases the installation rate in an area by one percent.

Two-stage least squares regression modelling is used to examine the diffusion of technologies which become available to households at different time periods. McCoy and Curtis (2016) investigate gas central heating adoption in Ireland, taking an instrumental variables approach to modelling the proportion of homes in census small areas that possess a connection to the gas network as a function of area characteristics and the modelled time since the introduction of the gas network to the area. They find an average 3% increase in gas connections for every year the gas network has been in place in an area, decreasing over time. Lyons (2014) investigates the take-up of broadband in Irish households, modelling the proportion of homes in an area adopting broadband after first modelling the introduction of broadband to an area, finding a high initial growth rate which reduces to the national average after 3.6 years.

Moya (2016) presents an "autoregressive moving average and regression model" (ARMAX) to analyse the diffusion of energy-efficient technologies, using a case study of the diffusion of electric arc furnaces in Japan. Noonan et al. (2013) use spatial econometric techniques to examine the adoption of energy efficient Heating Ventilation and Cooling (HVAC) systems in Greater Chicago and suggest that upgrading 90% of homes in a neighbourhood could lead to an increase in uptake in adjacent neighbourhoods by 3.4% of homes. In research specific to energy efficiency grant schemes, Song (2008) examines the spatial distribution of participants to a residential energy efficiency project in Ontario, Canada, and uses a count data model to estimate the number of participating households in an area as a function of area characteristics.

2.3. Drivers of household retrofitting activities

While a wide-ranging literature exists on the drivers of the household energy efficiency investment decision, we review solely the literature on drivers which may affect households heterogeneously but are ultimately determined outside the household. Specifically, we look at the literature on spillover effects, the impact of advertising, the role of subsidies and finally other policy tools. With regard to spillover effects, we have outlined above the findings of several papers which measure the effect of the installed base on adoption of solar PV in California (Bollinger and Gillingham, 2010) and the UK (Richter, 2013) and HVAC units in Chicago (Noonan et al., 2013).

With respect to advertising, as mentioned above, Hlavinka et al. (2016) find a positive relationship between expenditures on a combination of advertising, education and training for installers and the adoption of heat pumps, although the paper does not differentiate the effects of these individual expenditures. Diffney et al. (2013) examined the effectiveness of an energy efficiency advertising campaign on natural gas consumption in Ireland, finding short term reductions in gas consumption but no long term effects, though the research did not investigate whether advertising had any effect on gas boiler installations or other energy efficiency investments.

Research on the role of subsidies includes Neuhoff et al. (2012), who compare the effectiveness of subsidies across Italy, the Netherlands, Germany and the United States, finding that tax incentives as well as loans and grant aid led to a high take-up. Neuhoff et al. (2012) also find that countries which offered increasing levels of financial support for retrofits comprising greater numbers of measures had a higher take-up of comprehensive retrofits than those who offered a constant level of support for each measure, regardless of how many measures were undertaken. In a similar vein, although in a study of firm choice, Aalbers et al. (2009) find that a subsidy may entice managers to adopt certain technologies for the business even if the subsidy is not enough to make the adoption profitable as the presence of the subsidy itself invokes positive connotations.

2.4. Product growth models

Bass (1969) extended Roger's theoretical approach to product diffusion in a quantitative framework. New product growth models, commonly referred to as 'Bass models', seek to model the adoption of products over time, often with a view to forecasting sales. While originally intended for the analysis of the adoption of consumer durables, the model was subsequently applied across the retail, industrial and agricultural sectors and, in particular, was adapted to estimate the effects of advertising (Bass et al., 1994). Further extensions of the model have accounted for successive generations of technology and changes in the price of goods, services or technologies (Bass, 2004).

While the Bass model has hundreds of applications in the literature (Bass, 2004), this research is concerned with the diffusion of residential energy efficiency upgrades facilitated through a grant scheme. Lund (2006), for example, apply a diffusion model to analyse the penetration rates of eleven different energy technologies, finding that time required to progress from a market penetration of 1% to 50% can vary across products from ten to seventy years. Lesser time requirements were found with end-use products, such as CFL lamps, while longer times were associated with technologies providing greater energy savings, such as heat pumps. Higgins et al. (2011) model the uptake of solar water heating and solar PV in Brisbane, finding that a rebate of AU$8,000 was most effective in stimulating demand for solar PV among middle-income households. More recently, Hlavinka et al. (2016) estimate and forecast the adoption of heat pumps in the United States as a function of market potential, tax credits available, income and seasonality. They find a negative relationship between installation costs and adoption and a positive relationship between expenditures by the subsidy provider, which comprise advertising, and education and training for installers, and adoption. Wang et al. (2017) find that the adoption rate of commercial solar PV systems is much lower than that of residential systems in California. Islam (2014) examines the diffusion of photo-voltaic solar panels among households using stated preference data, developing a method to generate time series forecasts of diffusion from cross section choice experiment data.

2.5. Contribution

This paper examines the diffusion of energy efficiency up-grades across the housing stock. While there have been several applications of the Bass model to the diffusion of specific energy technologies (Higgins et al., 2011; Hlavinka et al., 2016; Islam, 2014; Wang et al., 2017), this analysis considers the diffusion of bundles of energy technologies encompassed within residential retrofits, which is a novel application of the Bass model. A specific contribution to the energy efficiency literature is providing empirical evidence of the impact of advertising and spillover effects from other energy efficiency investments on residential energy efficiency retrofits. This knowledge has particular relevance to governments and energy agencies that strive to improve residential energy efficiency. While there are numerous other drivers of household retrofitting activities, many of which are endogenous to the household, we do not consider them here.

3. Methodology

The instantaneous rate of adoption of an energy efficiency retrofit f at time t can be expressed using the following differential equation (Bass, 1969).

$$f(t) = [\alpha + \beta F(t)][1 - F(t)] \tag{1}$$

where α represents the coefficient of innovation, β the coefficient of imitation and F the proportion of all energy efficiency retrofit adopters who have done so by time t. The coefficients of innovation and imitation provide an explanation of the diffusion pattern. The importance of innovators will be greater early in the diffusion process but will diminish monotonically as t rises and is referred to as the innovation coefficient as it does not interact with the cumulative adoption function, while the coefficient of imitation reflects how previous adoptions impact the conditional likelihood of adoption. In cases where the coefficient of imitation is greater than that of innovation, the diffusion pattern will reach a peak before declining, while a larger coefficient of innovation corresponds with an ever-increasing diffusion pattern. Following Hlavinka et al. (2016), the solution to differential equation (1) gives the cumulative adoption F at time t:

$$F(t) = \frac{1 - e^{-(\alpha+\beta)t}}{1 + (\frac{\beta}{\alpha})e^{-(\alpha+\beta)t}} \tag{2}$$

With π being a household's probability of adoption and $F(t) - F(t-1)$ being the proportion of market potential adopting in the time interval $[t-1, t]$, the conditional probability of a household adopting during the same time interval subject to it not having previously undertaken an energy efficiency retrofit is

$$\frac{\pi(F(t)-F(t-1))}{1-\pi F(t-1)} \tag{3}$$

Total adoptions in the time interval, S_t, can therefore be expressed as a function of the conditional probability of household adoption, market potential, M, and cumulative adoptions at the beginning of the time interval, R_{t-1}, as follows:

$$S_t = (M - R_{t-1})\frac{\pi(F(t)-F(t-1))}{1-\pi F(t-1)} \tag{4}$$

A household's probability of adoption is typically modelled using a logistic expression as a function of exogenous explanatory variables, x_t (Fernandez, 2000; Hlavinka et al., 2016; Jain and Rao, 1990). In particular, Hlavinka et al. (2016) model π_t as a function of aggregate expenditures on advertising, education and training for technology installers. Typically, a logarithmic transformation is applied to the exogenous variables x_t and the estimated coefficients interpreted as elasticities of demand with respect to the variables x_t. We adapt this model in two ways. First, as some of our explanatory variables are binary we do not apply the logarithmic transformation and consequently the associated coefficients cannot be interpreted as elasticities. We calculate marginal effects instead. The second and more substantive adaptation is that we allow for spatial variation, modelling total adoptions by county, i, in the time interval $[t-1, t]$, $S_{i,t}$. Incorporating a spatial dimension allows for different diffusion pathways across counties. For instance, unobserved characteristics driving diffusion, such as income, may vary by county. The estimated model is specified as follows:

$$S_{i,t} = (M_i - R_{i,t-1})\frac{\pi_{i,t}(F(t)-F(t-1))}{1-\pi_{i,t} F(t-1)} \tag{5}$$
$$\pi_{i,t} = \frac{e^{(\gamma x_{i,t})}}{1+e^{(\gamma x_{i,t})}}$$

During estimation the variable x_t is specified as a linear function of several exogenous variables, including six types of advertising (e.g. print, radio, online, etc.). These variables and other data used to estimate the model are discussed in section (4).

While the estimated parameters α and β are of interest, the key issue of policy relevance is associated with the estimate of γ. For example, what is the marginal effect of advertising on the adoption of energy efficiency retrofits? Where a logarithmic transformation is applied to the exogenous variables $x_{i,t}$, the associated estimated coefficients are interpretable as elasticities of demand (Hlavinka et al., 2016). However, when the logarithmic transformation is not feasible, as is the case for binary variables (e.g. indicating the presence or absence of online advertising) direct interpretation of γ is not straightforward. Instead we calculate discrete marginal effects, Δ, as follows:

$$\Delta = \sum_i (S_{i,t}|_1 - S_{i,t}|_0) \tag{6}$$

where $S_{i,t}|_0$ represents an estimate of total adoptions in the baseline case, e.g. absence of online advertising, and $S_{i,t}|_1$ represents an estimate of total adoptions in the policy case, e.g. presence of online advertising. The summation over counties, i, in equation (6) provides a single marginal effect across all counties. Confidence intervals for the discrete marginal effects estimates are calculated using 10,000 drawings of the parameter vector based on the estimated variance-covariance matrix similar to the approach suggested by Krinsky and Robb (1986).

4. Data

SEAI administers the BEH scheme, a grant aid scheme to encourage energy retrofits in residential properties built prior to 2006. We use an administrative dataset of all applications made to the BEH scheme in the period

March 2009 to December 2015. Grants are available for roof/attic insulation, one of three types of wall insulation (cavity insulation, external wall insulation or internal dry-lining), three types of heating system upgrade (oil boiler or gas boiler with heating controls upgrade or heating controls upgrade only) and solar collector (panel or tube) installation. This means that a household may adopt up to a maximum of four measures as only one type of wall insulation or heating system upgrade may be awarded grant aid. Upgrades must satisfy SEAI technical standards for grant applications to be successful.

The model is estimated for two classes of retrofit grant applications. In the first the dependent variable, $S_{i,t}$, is the total number of private applications to the BEH scheme per month in each county, conditional on these homes not having previously applied to the scheme in the past. In the second the dependent variable is similar but in this instance includes only non-abandoned grant applications. Figure 1 details the adoption of Better Energy Homes retrofits over time, showing monthly applications and monthly "non-abandoned" applications, as not all applications result in completed retrofits. Also included in Figure 1 are cumulative completed retrofits. The figure illustrates the seasonality in applications, while a large structural break appears to occur after November 2011 coinciding with the financial bailout of the Irish State by the European Commission, the European Central Bank and the International Monetary Fund, and the subsequent recession.

Applications to the grant scheme are generally made privately, with a household first contacting an SEAI registered contractor, before applying for the grant. Some applications are made via 'obligated parties' who are energy distributors and retail energy sales companies that are required to achieve certain energy targets under the Energy Efficiency Obligation Scheme, pursuant to the EU Energy Efficiency Directive (European Parliament and the Council of the European Union, 2012), and in Ireland 20% of which must be achieved by reducing residential energy consumption. We include applications via obligated parties in our total number of completed applications, which affects market potential at each time period, but we do not include these in our dependent variable. This is because we do not possess information on advertising from these parties or other subsidies offered directly to consumers. Our analysis is therefore confined to private energy efficiency grant applications.

Market potential, M, is measured as the number of qualifying homes who have not previously engaged in a BEH retrofit. We use the stock of owner-occupied properties in each county, as recorded in the 2006 census of population (CSO, 2007). The BEH scheme only provides grant aid to properties built prior to 2006. The cumulative adoptions in county i at the beginning month t, $R_{i,t-1}$, comes directly from the BEH administrative dataset.

In addition to county and month dummy variables the remaining explanatory variables included in model estimation are data on BEH scheme advertising as well as retrofits through a parallel retrofit scheme, the *Better Energy Communities* scheme (BEC). SEAI also administer the BEC scheme, which provides grant aid for the thermal retrofit of a cluster of homes and public buildings within a community. A BEC scheme application comprises a single community led application for energy efficiency retrofits of specific private and community buildings within a locality. It is not unreasonable to assume that public awareness of the benefits of energy retrofits increases in the proximity of a BEC application, as people discuss the application, attend meetings, as well as through media coverage. We hypothesise that the increased awareness of the benefits of energy retrofits due to BEC application has a positive spillover effect on BEH applications within the wider community and its environs. We include the number of homes retrofitted as part of a BEC scheme within each county within the prior three months as an exogenous variable in our model of BEH grant applications. Mean monthly applications to both the BEH and BEC scheme are reported in Table 1.

Since the introduction of the BEH scheme SEAI have engaged in various advertising campaigns to promote the scheme. These have included outdoor advertising, online advertising on various social media, news and property-related websites, print advertising in both local and national newspapers and radio advertising on both local and national stations. National and online advertising is present in all counties, whereas local print and radio, as well as outdoor advertising is county specific. Data on the scale or intensity of advertising (e.g. broadcast minutes, or advertising budget) is required to elicit a good estimate on the impact of advertising on retrofits. Unfortunately, such detailed data was not available and instead the analysis relied on data indicating the presence or absence of different types of advertising. Consequently, the estimates of the marginal impact of advertising should be interpreted with caution and considered as rough approximations. Details of the timing and medium of advertising of the scheme is provided in Appendix A.

Figure 1: Adoption of residential energy efficiency retrofits under the Better Energy Homes scheme

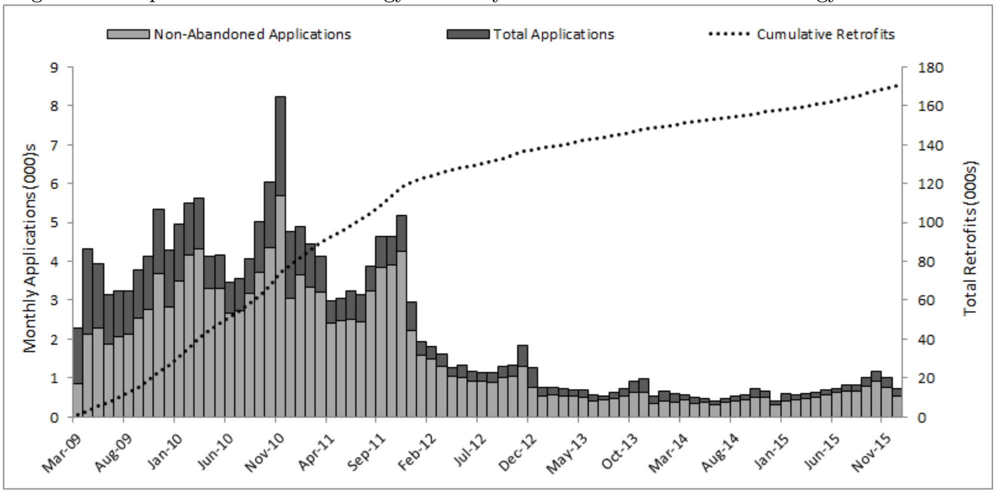

Table 1: Mean monthly application to Better Energy Homes (BEH) and mean monthly number of retrofits installed under Better Energy Communities (BEC) schemes

	Applications		Non-Abandoned Applications		BEC Retrofits in previous 3 months	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Jan	87.02	115.73	62.14	85.57	17.36	54.93
Feb	86.54	117.16	63.90	88.33	17.38	136.29
Mar	84.98	114.41	58.69	86.53	11.70	124.96
Apr	79.80	99.69	54.34	68.45	9.06	124.38
May	78.56	98.28	55.87	71.15	0.00	0.00
Jun	69.57	90.07	49.33	65.07	0.00	0.00
Jul	70.49	89.03	50.69	64.67	0.00	0.00
Aug	78.30	108.33	58.24	84.24	0.50	6.62
Sep	92.86	125.01	68.30	95.20	5.47	55.13
Oct	102.77	136.80	74.55	103.71	6.74	56.30
Nov	126.60	170.94	89.04	124.79	26.16	98.00
Dec	80.95	110.30	52.92	74.62	25.59	69.21

5. Estimation and Results

5.1. Estimation

For estimation, we follow the non-linear squares (NLS) estimation approach for the Bass model proposed by Srinivasan and Mason (1986). Srinivasan and Mason's model provides more valid estimates of standard errors for the parameter estimates than several other estimation procedures, including ordinary least squares (OLS) and maximum likelihood estimation (Mahajan et al., 1986; Satoh, 2001). To allow for the possibility of serial correlation in errors between successive periods, we assume autocorrelated errors with an AR(1) process for the error term (Hlavinka et al., 2016; Talukdar et al., 2002). We do not find any substantial differences in the parameter estimates between the models where autocorrelation is accounted for or not. The standard errors for most of the parameters estimates in the model where autocorrelation is accounted for are lower, but it has no practical impact on the inferences that we make.

The model is estimated for two classes of retrofit grant applications. In the first the dependent variable is the total number of private applications to the BEH scheme per month by county, conditional on these homes not having previously applied to the BEH scheme. In the second model the dependent variable is applications that are not subsequently abandoned, i.e. non-abandoned applications. Through the two model estimates we will be able to isolate how advertising generates initial interest in energy retrofits (i.e. via all grant applications) and a smaller number of households that actually undertake a retrofit. The parameter estimates are reported in Table 2.

5.2. Bass model parameter estimates

While the parameter estimates are case specific, there are similarities with prior empirical studies. Estimates of coefficients of innovation (α) and imitation (β) of 0.01 and 0.05 respectively are quite similar to those estimated by Hlavinka et al. (2016) examining diffusion of heat pumps in the United States and Wang et al. (2017) investigating adoption of photovoltaic systems in California. These estimates suggest that while there are 'innovators' that unilaterally undertake residential energy retrofits, the majority are influenced by neighbours and friends that have previously invested in retrofits. The estimates of α and β are relatively low compared to estimates for many consumer products such as electronics or appliances (Sultan et al., 1990), which reflects a much longer time horizon for the diffusion of residential energy retrofits across the housing stock. For instance, in Sultan et al.'s meta-analysis of Bass model estimates the average estimate for α is 0.03 and 0.38 for β. Estimates of β vary substantially between studies/products but the higher value estimates often arise in consumer electronics, though investigating flat-screen televisions in Europe Peers et al. (2012) estimate a value of 0.07 for β.

5.3. Advertising

As noted earlier, direct interpretation of the associated parameter estimates is not straightforward. Instead, we discuss the associated discrete marginal effects, Δ, which are reported in Table 3. Six types of advertising are distinguished within the model but the calculated marginal effects are statistically significant only for two cases: national print advertising and online advertising. Local print and outdoor billboard advertising was undertaken for less than one month in each case so it is not unexpected that the estimated marginal effects are not significant. However, this result relates only to advertising paid for by SEAI and excludes other content on energy efficiency within print or broadcast media, such as advertising by building and energy contractors or news features on energy efficiency. Also, as mentioned when describing the data, the advertising variables measure presence or absence of advertising during a particular month rather than intensity of advertising, which means that we should exercise caution in interpreting the results. Consequently, where there is no measurable impact in terms of additional grant applications attributable to SEAI's advertising activities we should assume that absence of evidence is not evidence of absence. Further research based on more detailed data is required to investigate the efficacy of local print or broadcast advertising.

Advertising in national print media has a substantial estimated impact on grant applications. Over the term of the BEH scheme a maximum of 804 additional grant applications per month are attributed to national print advertising. More recently, the impact is substantially less with a mean of 38 additional applications per month during in 2015. The dramatic drop bridges the period of the financial bailout of the Irish State and the subsequent recession. The net impact of advertising is somewhat less, as just a mean 17 additional applications per month were made during 2015 that were not subsequently abandoned. There is a similar marginal impact from online advertising with 80 additional monthly applications during 2015, of which an average of 35 were not not subsequently abandoned. Again, as the data on advertising measures presence of rather than intensity of advertising content caution must be exercised in interpreting the results. National print and online advertising

Table 2: Estimated results of effects on retrofit adoption

		Applications		Non-Abandoned Applications	
		(1)		(2)	
α	("coefficient of innovation')	0.0161***	(0.000493)	0.0126***	(0.000476)
β	("coefficient of imitation')	0.0538***	(0.00281)	0.0624***	(0.00306)
Constant		-1.167***	(0.0570)	-1.517***	(0.0649)
Outdoor Advertising		0.0968	(0.0826)	0.0880	(0.0863)
Local Print Advertising		-0.116	(0.128)	-0.0300	(0.137)
National Print Advertising		0.176***	(0.0580)	0.124**	(0.0627)
Local Radio Advertising		-0.402	(0.271)	-0.352	(0.318)
National Radio Advertising		0.198	(0.267)	0.216	(0.314)
Online Advertising		0.354***	(0.0419)	0.250***	(0.0434)
No. of BEC Homes		0.000553*	(0.000303)	0.000606**	(0.000297)
Seasonality					
February		0.0117	(0.0447)	0.0222	(0.0498)
March		-0.0574	(0.0567)	-0.0514	(0.0656)
April		-0.313***	(0.0437)	-0.311***	(0.0446)
May		-0.216***	(0.0372)	-0.207***	(0.0386)
June		-0.318***	(0.0457)	-0.323***	(0.0466)
July		-0.343***	(0.0436)	-0.351***	(0.0478)
August		-0.373***	(0.0595)	-0.269***	(0.0670)
September		-0.203***	(0.0497)	-0.131**	(0.0527)
October		0.160***	(0.0572)	0.164***	(0.0515)
November		0.443***	(0.0514)	0.380***	(0.0536)
December		-0.00248	(0.0547)	-0.0934*	(0.0554)
Structural Break		-0.519***	(0.0696)	-0.582***	(0.0763)
County Fixed Effects (ref=Dublin city)					
Carlow		-0.308***	(0.0532)	-0.335***	(0.0648)
Cavan		0.239***	(0.0622)	0.181***	(0.0620)
Clare		0.680***	(0.0615)	0.725***	(0.0630)
Cork		-0.00336	(0.0417)	0.0585	(0.0485)
Donegal		-0.268***	(0.0717)	-0.375***	(0.0650)
County Dublin		-1.663***	(0.0392)	-1.655***	(0.0470)
Galway		0.409***	(0.0471)	0.419***	(0.0486)
Kerry		0.426***	(0.0587)	0.428***	(0.0635)
Kildare		-0.712***	(0.0402)	-0.773***	(0.0479)
Kilkenny		-0.107*	(0.0637)	-0.0854	(0.0662)
Laois		-0.312***	(0.0537)	-0.280***	(0.0591)
Leitrim		-0.400***	(0.0615)	-0.525***	(0.0678)
Limerick		0.424***	(0.0469)	0.481***	(0.0514)
Longford		0.0271	(0.0775)	-0.0118	(0.0892)
Louth		-0.318***	(0.0471)	-0.337***	(0.0508)
Mayo		-0.154***	(0.0492)	-0.201***	(0.0571)
Meath		-0.658***	(0.0489)	-0.716***	(0.0546)
Monaghan		0.189***	(0.0582)	0.184***	(0.0571)
Offaly		-0.602***	(0.0664)	-0.669***	(0.0687)
Roscommon		-0.0824	(0.0512)	-0.138**	(0.0565)
Sligo		-0.320***	(0.0566)	-0.385***	(0.0556)
Tipperary		0.0589	(0.0478)	0.114**	(0.0528)
Waterford		0.271***	(0.0420)	0.327***	(0.0515)
Westmeath		-0.392***	(0.0559)	-0.458***	(0.0597)
Wexford		0.0956	(0.0632)	0.149**	(0.0646)
Wicklow		-0.759***	(0.0495)	-0.774***	(0.0572)
AR(1)		0.00187***	(0.000223)	0.00231***	(0.000368)
Observations		2,214		2,214	
R-Squared		0.928		0.915	

Robust standard errors in parenthesis (*** $p < 0.01$, ** $p < 0.05$,* $p < 0.10$).

has a measurable impact on grant applications but we cannot estimate a conversion rate, such as application per unit advertising.

Across the entire BEH scheme the application abandonment rate is 15% (Collins and Curtis, 2017) compared to rates closer to 55% for marginal applications attributed to advertising from Table 3. This suggests that households influenced by advertising to apply for energy retrofit grants may possess less commitment to follow retrofits through to fruition than other applicant households. This suggests that any metric used to measure the efficiency of advertising activity should focus on additional successful grant applications rather than all additional applications. Alternatively, additional supports to home owners should be considered to avert abandonment of applications.

5.4. Spillover effects

The BEC scheme provides grant aid for the energy retrofit of private and community buildings within a locality through a single community led application. The BEC and BEH schemes run in parallel and are both administered by SEAI. The statistically significant marginal effect related to the BEC scheme in Table 3 provides evidence of a spillover effect between the two schemes. The marginal effect in Table 3 appears small but in context is relatively large. The calculated marginal effect relates to a single BEC application, which has mean of 86 buildings retrofitted. The marginal effect on BEH applications is 10 applications per month during 2015, with 7 of those applications being successfully completed. Spillover effects from a specific BEC application are likely to occur over several several months. In the construction of our model we assumed that the spillover effect would occur up to 3 months later (i.e. BEC applications in prior 3 months potentially have impact of number of applications in current month). Over a 3 month period that adds to 21 applications successfully completed, or approximately 25% of the size of the original BEC application. Our assertion is that the spillover between the BEC and BEH schemes arises through home owners that did not participate in a BEC application becoming aware of the benefits of energy retrofits from their neighbours participating in the BEC application, as well as through local media coverage. For every four properties retrofitted within a BEC application the results suggests that there is one additional successful application through the BEH scheme.

What is also noteworthy is that proportion of marginal applications that are subsequently abandoned is substantially lower than the comparable ratios for advertising (i.e. 30% versus 50%). We have no evidence why this is so but one potential explanation is that marginal applicants attributed to the BEC are better informed both of the benefits and costs of energy retrofits, including non-monetary costs such as disruption, prior to their application than other marginal applicants influenced by advertising and therefore are less likely to face unpleasant surprises during the application process triggering abandonment of their application.

5.5. Other explanatory variables

The remaining parameter estimates in Table 2 fall into two categories: seasonality and regional parameters. The monthly dummy parameter estimates directly reflect the seasonal trend in retrofit grant applications, with the highest applications at the start of winter, followed next by early spring and lowest applications occurring during the summer months. Instead of monthly dummies we also estimated the models with variables for mean monthly temperature but did not find plausible parameter estimates. The parameter estimates associated with individual counties illustrates the regional variations in grant applications, which may reflect important unobserved drivers of grant applications. Income might ordinarily be considered an important factor in this regard, as grants only account for approximately 30% of retrofit measure costs, potentially leading to higher levels of grant applications from areas with higher income levels. However, the sign and relative magnitude of the estimates related to specific counties are not consistent with their relative mean income levels.

Table 3: Marginal effects, applications per month

	Applications			Non-abandoned applications		
	Maximum	Minimum	Jan-Dec 2015†	Maximum	Minimum	Jan-Dec 2015†
Outdoor advertising	440	14	21	287	8	12
	(-5 – 1107)	(-161 – 36)	(-8 – 54)	(-5 – 811)	(-186 – 23)	(-7 – 35)
Local print advertising	-15	-485	-23	-2	-88	-4
	(-38 – 442)	(-1278 – 15)	(-57 – 22)	(-19 – 702)	(-740 – 20)	(-29 – 31)
National print advertising	804*	25*	38*	416*	11*	17*
	(361 – 1273)	(12 – 41)	(18 – 61)	(68 – 772)	(2 – 20)	(3 – 32)
Local radio advertising	-47	-1574	-71	-26	-1028	-41
	(-87 – 195)	(-2959 – 6)	(-130 – 9)	(-56 – 553)	(-2180 – 15)	(-86 – 23)
National radio advertising	926	30	45	743	20	31
	(-31 – 3323)	(-985 – 111)	(-47 – 166)	(-23 – 2941)	(-851 – 83)	(-35 – 129)
Online advertising	1650*	53*	80*	849*	23*	35*
	(1307 – 2006)	(39 – 71)	(60 – 104)	(604 – 1115)	(15 – 33)	(23 – 50)
BEC homes	209*	7*	10*	172*	5*	7*
	(23 – 408)	(1 – 13)	(1 – 19)	(32 – 313)	(1 – 8)	(1 – 13)

† Jan-Dec 2015 are the final 12 months of the dataset. Reported marginal effects are the monthly mean.
90% confidence intervals in parenthesis, * $p < 0.10$.

6. Conclusion and Policy Implications

The BEH scheme financially supports households undertaking energy efficiency retrofits. The objective of the scheme is to improve the residential building stock's energy efficiency and consequently reduce energy consumption. A better understanding of the factors that drive residential energy retrofits, as well as applications for supporting financial aid, would inform how energy efficiency grant support schemes might be more effectively implemented. This paper focuses on two drivers exogenous to households but which potentially affect their propensity to undertake energy retrofits, namely advertising and spillover from spending in other energy retrofit schemes. The analysis employs the well established Bass model of technology diffusion to examine the dispersion of retrofits across the housing stock.

We find evidence of a strong spillover between retrofit grant schemes. Energy retrofits undertaken through a community application scheme (i.e. BEC) lead to additional applications in the private applications scheme (i.e. BEH). Our estimates suggest that for every four buildings retrofitted within the community scheme (both private and community buildings) one additional private retrofit is subsequently completed with grant support from the BEH scheme. From a policy perspective this suggests that community involvement could be an important lever in encouraging homeowners to retrofit their properties.

We find mixed evidence on the impact of advertising on retrofit grant applications. National print and online advertising has a measurable impact on grant applications but given the nature of the advertising data we use we cannot estimate a conversion rate, such as application per unit advertising. In the case of advertising with local print or broadcast media we suggest that absence of evidence is not evidence of absence (of an effect of advertising). Future research with more detailed advertising data is necessary to investigate this issue more thoroughly. However, the findings in relation to the BEC scheme suggests that relevant information from the locality may play an important role in encouraging residential retrofits and local media outlets have a role to play in disseminating such information. In conclusion, these findings suggest that the grant provider should focus on online and national print advertising to drive retrofits. However, there is insufficient evidence here to discount local or broadcast media channels, especially when disseminating the experiences from local community led retrofits.

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Appendix A. Advertising Schedule

Table A.4: Advertising Schedule

Year	Weeks Commencing	Details
		Outdoor Advertising
2011	25-Jul - 1-Aug	Advertising panels in Dublin, transit rectangles in Drogheda, Dundalk, Navan, Athlone, Sligo, Galway, Limerick, Tralee, Cork, Waterford, Rosslare
		Local Print Advertising
2012	04-Jun - 18-Jun	Advertising in 28 Local Papers Across Ireland
		National Print Advertising
2009	23-Mar	Irish Times, Sunday Times, Irish News of the World, Sunday World
	30-Mar	Irish Times, Irish Independent, Irish Daily Star
2010	12-Jul	Irish Times, Sunday Times, Irish Independent, Sunday Independent
	19-Jul	Irish Times, Sunday Times, Sunday World, Irish Daily Star
	26-Jul	Irish Times, Sunday Independent, Sunday World
2011	18-Jul	Sunday Independent
	25-Jul	Irish Times, Irish Independent, Irish Daily Star, Irish Sun
	01-Aug - 08-Aug	Irish Times, Irish Independent, Irish Daily Star
2012	04-Jun - 18-Jun	Irish Times, Irish Independent, Irish Examiner, Sunday World, Irish Daily Star
2013	11-Nov - 18-Nov	Irish Times, Irish Independent, Irish Examiner
	25-Nov	Irish Times, Irish Independent
	02-Dec	Irish Times
2014	03-Feb - 10-Feb	Irish Times, Irish Independent, Irish Examiner
	17-Feb - 24-Feb	Irish Times
	10-Mar - 07-Apr	Irish Independent
	05-May	Irish Times, Irish Examiner
	12-May	Irish Times, Irish Independent, Irish Examiner
	19-May	Irish Times, Irish Independent
	26-May	Irish Times, Irish Independent, Irish Examiner
	02-Jun	Irish Independent
	04-Aug	Irish Examiner
	11-Aug	Irish Independent, Irish Examiner
	18-Aug	Irish Times, Irish Examiner
	25-Aug	Irish Times, Irish Independent, Irish Examiner
	08-Sep	Irish Independent
		Radio Advertising
2009	06-Apr	RTE 1, 2FM, Local Radio
	13-Apr	2FM, Local Radio
2010	12-Jul	RTE, Newstalk
	19-Jul	RTE 1, Local Radio
	26-Jul	Today FM, Local Radio
2011	18-Jul	RTE 1
	25-Jul	RTE 1, Local Radio
	01-Aug - 08-Aug	Today FM, Local Radio
2012	29-Oct - 05-Nov	RTE 1, Newstalk, Today FM, Local Radio
2013	11-Nov - 02-Dec	RTE 1, 2FM Today FM, 4FM, Local Radio
2014	03-Feb	Today FM, 4FM, Local Radio
	10-Feb - 24-Feb	RTE 1, 2FM, Today FM, 4FM, Local Radio
	03-Mar	RTE 1
		Online Advertising
2009	30-Mar - 13-Apr	Irish Times, Irish Independent, Daft, MyHome
	20-Apr	MyHome
2010	12-Jul - 2-Aug	Pay Per Click, MyHome
2011	18-Jul - 8-Aug	Daft, MyHome, RTE
2013	7-Oct - 4-Nov	Pay Per Click
	11-Nov - 1-Dec	Pay Per Click, Irish Times, Irish Independent, Daft, BBC, RTE, The Journal, AA, Homemaker Channel, Twitter
	9-Dec - 30-Dec	Pay Per Click
2014	3-Feb - 5-May	Pay Per Click
	12-May - 9-Jun	Pay Per Click, Crimtan, Accuen, Digitize
	16-Jun - 4-Aug	Pay Per Click
	11-Aug - 15-Sep	Pay Per Click, Crimtan, Accuen, Digitize
	22-Sep - 24-Nov	Pay Per Click
2015	3-Aug - 21-Sep	Pay Per Click
	28-Sep - 31-Oct	Pay Per Click, Accuen, YouTube

Year	Number	Title/Author(s) ESRI Authors and Affiliates *Italicised*
2017		
	568	Working at a different level? Curriculum differentiation in Irish lower secondary education *Emer Smyth*
	567	Identifying rent pressures in your neighbourhood: a new model of Irish regional rent indicators *Martina Lawless, Kieran McQuinn and John R. Walsh*
	566	Who pays for renewables? Increasing renewable subsidisation due to increased datacentre demand in Ireland *Muireann Á. Lynch and Mel T. Devine*
	565	Can tenants afford to care? Investigating the willingness-to-pay for improved energy efficiency of rental tenants and returns to investment for landlords *Matthew Collins and John Curtis*
	564	Female participation increases and gender segregation *Claire Keane, Helen Russell and Emer Smyth*
	563	Pike (Esox lucius) stock management in designated brown trout (Salmo trutta) fisheries: Anglers' preferences *John Curtis*
	562	Financial incentives for residential energy efficiency investments in Ireland: Should the status quo be maintained? *Matthew Collins, Seraphim Dempsey and John Curtis*
	561	Does a satisfied student make a satisfied worker? *Adele Whelan and Seamus McGuinness*
	560	The changing relationship between affordability and house prices: a cross-country examination *Kieran McQuinn*
	559	The role of community compensation mechanisms in reducing resistance to energy infrastructure development *Marie Hyland and Valentin Bertsch*
	558	Identification of the information gap in residential energy efficiency: How information asymmetry can be mitigated to induce energy efficiency renovations *Matthew Collins and John Curtis*

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