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Access to and consumption of natural gas: spatial and socio-demographic drivers

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Abstract: In the context of reducing greenhouse gas emissions in the residential sector, fuel switching from coal and oil to natural gas is considered as a policy option. The paper considers fuel choice decisions among households within 30 metres of the Irish natural gas network. Consistent with earlier research a range of building attributes and household characteristics are associated with fuel choice for household space heating. Additionally, there are substantial distance decay effcts with respect to gas network connection within relatively close proximity to the network, meaning that properties further distant from the gas network are less likely to be gas customers. The distance decay effects are likely attributed to network connection fees, which are proportional to the connection distance. The paper simulates the impact of eliminating distance decay effects, i.e. the marginal connection cost associated with distance is set to zero, and examines emission and expenditure impacts across socio-economic groups. The analysis finds that up to 13% of unconnected properties are likely to respond to such an incentive, yielding a 3.9% reduction in greenhouse gas emissions and a 1.5% reduction in fuel expenditure relative to pre-policy levels of unconnected households within the study. Expenditure and emission impacts differ across socio-economic groups with the largest reductions expected to occur among semi-skilled/unskilled households, which are frequently among the least affluent households. Though counter-intuitive, greenhouse gas emissions from the residential sector could be reduced by incentivising connections to the natural gas network.

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1. Introduction

Policy interest in residential energy demand, including how access to grid supplied natural gas impacts on demand for other fuels, has a long history (e.g. Halvorsen, 1975; Houthakker, 1951; Blattenberger et al., 1983). Recent public policy attention on climate change and efforts to reduce greenhouse gas emissions has led to a renewed focus on residential heating fuel choice decisions. Households' domestic heating systems and the carbon intensity of the associated fuels, along with the level of energy service demand, are key factors affecting overall environmental quality. Carbon dioxide (CO_2) emissions, predominantly from coal, oil and gas in western countries, contribute to substantial climate change related environmental externalities. In the European Union about 16% of CO_2 emissions are estimated to occur in residential buildings, where space and water heating account for 67% and 14% of residential energy consumption, respectively (European Commission, 2011a,b). Similarly, in the United States roughly one-quarter of energy consumption occurs in residential buildings (U.S. Department of Energy, 2012, Table 1.1.3). Hence, improved knowledge of households' decisions around heating systems, as well as, the factors that determine the choice of these systems are of relevance for climate mitigation policies. Understanding what drives households to make (or not make) such decisions will help policy-makers better design incentives to encourage transition to low-carbon residential heating systems.

Prior research on residential energy demand is wide ranging, though disproportionately focuses on network fuels (i.e. natural gas and electricity), which possibly reflects data availability (e.g. Halvorsen, 1975; Houthakker, 1951; Blattenberger et al., 1983; Filippini, 1999; Holtedahl and Joutz, 2004; Dergiades and Tsoulfidis, 2008; Harold et al., 2015). Though other residential fuels such as firewood, oil, liquefied petroleum gas, etc., have also been studied (e.g. Kayacan et al., 2012; Garbacz, 1984; Wadud et al., 2010; Garbacz, 1985; Lillemo and Halvorsen, 2013; Couture et al., 2012; Arabatzis and Malesios, 2011). The majority of demand studies are country specific, with some cross-country comparisons (e.g. Krishnamurthy and Kriström, 2015; Pindyck, 1980). Whether the studies concentrate on residential energy demand or the narrower subject of space-heating fuel demand (e.g. Meier and Rehdanz, 2010; Nesbakken, 2001), a common research focus is the estimation of price elasticities of demand (e.g. Labandeira et al., 2017; Okajima and Okajima, 2013), which have relevance for policymakers and energy suppliers. Another research focus is examining how policy efforts to improve energy efficiency impact on energy demand (e.g. Haas and Schipper, 1998; Cebula, 2012; Filippini and Hunt, 2012).

While energy demand studies are usually conditional on socio-demographic characteristics, a parallel research strand focuses specifically on non-price drivers associated with residential energy demand. For example, Allcott (2011) examines how communicating social norms impacts on energy consumption. Or examinations of how behavioural interventions (e.g. home energy audits; historical or peer comparison, etc.) impact on household energy use (e.g. Delmas et al., 2013; Allcott and Rogers, 2014; Frederiks et al., 2015). This paper is positioned within the literature examining key building and occupant attributes associated with varying levels of residential fuel access and demand. Price and income are critical determinants of demand but other factors play an important role, which is the focus here. Even in the case of income the empirical findings are mixed. The use of oil and coal is more often associated with lower income home-owners (Fu et al., 2014; Laureti and Secondi, 2012; Özcan et al., 2013) though in many cases income effects are negligible or absent (Braun, 2010; Lillemo et al., 2013; Couture et al., 2012).

Several factors have been identified as being associated with use of specific residential fuels, including supply proximity, education, economic status, age, as well as property age, size and type. Where there are indigenous or local fuel supplies, particularly peat or firewood, cultural norms impact on fuel choice (Couture et al., 2012; Laureti and Secondi, 2012; Fu et al., 2014). Access to natural gas networks play an important role in fuel choice decisions across several countries. Mansur et al. (2008) find that US households with gas network access make different consumption choices compared to those without access. In France Couture et al. (2012) model residential fuel choice and find that gas network access increases the likelihood that a property uses gas as the primary source of energy by 8 percentage points, with oil being the fuel that is displaced to the greatest extent. In Ireland Fu et al. (2014) find that the likelihood of solid fuels being the primary residential heating source declines by 4 percentage points in areas within a threshold distance of the natural gas network, and more recently Curtis et al. (2018) find that households aware of a possibility of a local network connection are 59 percentage points more likely to choose gas when upgrading their heating system compared to respondents not aware of the accessibility of the network gas. Also in Ireland McCoy and Curtis (2018) find that even where the gas network is readily accessible that distance to network matters. A 1 percent increase in average distance to the network is associated with a 12 percentage point reduction in the proportion of users in the local area connected to the network. The reason distance matters to homeowners is that connection fees are proportional to the connection distance.

The association between economic status, education, income and age with residential fuel type are broadly similar; households with higher levels of these attributes are generally further up the so-called 'energy ladder' of cleaner, more efficient fuels (Hosier and Dowd, 1987). For example, Özcan et al. (2013) find that household heads aged 50 and above are more likely to choose gas, oil and electricity compared to coal and other solid fuels for reasons of ease of use and for health concerns. But findings are often case specific, with multiple studies finding no association between fuel type and age, education nor income (Decker and Menrad, 2015; Curtis et al., 2018). Property age is often associated with specific fuel types (Laureti and Secondi, 2012; Michelsen and Madlener, 2012) whereas property size and type are more relevant in others (Michelsen and Madlener, 2016). Beyond socio-demographic drivers of fuel choice decisions, Curtis et al. (2018) additionally consider whether home-owners' environmental knowledge or behaviours are associated with more sustainable choices surrounding home heating systems, specifically lower CO_2 emissions intensity. Even among home-owners actively making decisions about home heating, their environmental knowledge/behaviours have little explanatory power related to their heating choices. This reflects wider research that finds pro-environmental attitudes do not always foster pro-environmental behaviour (Poortinga et al., 2004; Schultz and Zelezny, 1999; Finger, 1994).

This paper makes a number of contributions. First, it adds to the literature examining residential heating decisions. With respect to gas, we specifically examine distance decay effects, i.e. how distance to the network affects connection to gas. As noted earlier, research findings are generally case or country specific, therefore, further studies of this nature contribute to the body of knowledge in this field. Second, the paper introduces an innovative analysis quantifying the expected net effect on greenhouse gas emissions from a transition towards less carbon intensive residential heating fuels. Third, it identifies the distributional effects of increasing gas access and suggests possible policies to achieve this goal. And finally, the analysis provides practical guidance both to policy makers and industry practitioners involved in driving the energy transition. It quantifies where new connections to the natural gas network can lead to a substantial reduction in greenhouse gas emissions, both in the short and longer term, plus help focus the design of fuel switching incentives to achieve the greatest reduction in emissions.

A brief summary of our research findings are that poorer households and those in rented properties are less likely to use gas, while the greater the distance to the gas network, the smaller the probability of gas connection, which confirms previous research. Increasing the number of dwellings connected to the gas network has the potential to reduce emissions if households switch from more carbon intensive fuels. Based on a scenario that fixes the gas connection fee to a flat rate irrespective of distance, which leads to an increase in the probability of gas network connection, we estimate a 3.9% reduction in emissions from currently unconnected households within 30 metres of the gas network. There is an associated reduction in expenditure on heating fuels of 1.5%. These results suggest that the policy goals of reducing inequality and protecting the environment can be jointly targeted in this instance.

The paper is organized as follow: in section 3 we describe the methods and data used in the estimation. In section 4 we provide empirical analysis of current gas consumption and simulations on changes in the emission and heating expenditure when unconnected dwellings switch to the gas network. We also provide in section 5 a policy discussion and in section 6 we conclude.

2. Background

3. Material and methods

3.1. Data description

The data for the analysis comprises anonymised household level data on gas network connection, gas consumption, property attributes, and household socio-demographic characteristics. The detailed household-level information is a major advantage of our dataset, as research microdata that combines distance to the gas network and gas consumption are rare. The Central Statistical Office (CSO) of Ireland created the research data file, which entailed merging the 2016 census of population records at household level, which includes information both on household occupants and property attributes, with data from the gas network operator, Gas Network Ireland (GNI). The latter includes distance to gas network, network connection, and consumption information. Each observation represents one residential unit with information on the main fuel used for central heating, distance between the property and the gas network, property attributes and household characteristic variables. Gas consumption data is obviously only available for premises connected to the gas network and we account for this selection aspect in our econometric specifications. In construction of the dataset gas consumption data was matched with census records at building level, which means that it was not always possible to definitively match consumption records with the associated households in multi-household buildings, e.g. apartments. Consequently the dataset excludes households situated in multi-family properties (e.g. apartments) that could not be separately identified. The dataset also excludes properties beyond 30 metres distance from the gas network. As the dataset was specifically constructed to examine residential connections to the gas network, and as relatively few residential properties connect beyond that distance (largely attributed to a connection fee exceeding €1000 beyond 30m) the dataset was truncated at 30 metres distance. The dataset contains records for 466,929 households after data cleaning for missing observations, etc.. Table 1 summarises the descriptive statistics of the main variables that were included in the analysis. Based on the census of population data, the majority of households use gas as their main heating fuel (77 percent), 17 percent use oil, while lower proportions use solid fuels or electricity. From official gas consumption data 19 percent of the sample are not gas consumers, which is obviously less than the 23 percent from census records. This difference is reconciled by the fact that some households use other fuels as the primary fuel for central heating but use natural gas as a secondary heating fuel or for other purposes (e.g. cooking). Some 55 percent of the buildings are less than 15 metres distant from the network, 31 percent are between 15 and 20 metres, while the remaining 14 percent are located within a range of 20–30 metres.

The dataset just described has no information on energy consumption levels (with exception of gas). To explore the impact of transition to gas we utilise a national residential consumption survey, the Household Budget Survey (HBS), also compiled by the Central Statistical Office (CSO). The 2015-2016 HBS dataset is employed to impute household energy consumption in kilowatt hours (kWh) using prices for different fuels to convert expenditure from monetary terms to kWh.

3.2. Methodologial approach

The analysis is organised into two main parts. In the first part, we analyse the types of fuel that currently supply residential buildings and fuel consumption. This analysis identifies what fuels are consumed and what is the level of emissions and expenditures of Irish households for energy. With respect to gas connection we investigate distance decay effects, i.e. the household connection rate to the gas network declines with distance (Nekola and White, 1999; Choi, 2013; Knapp and Ladenburg, 2015). In the second part we implement a micro-simulation exercise, where we assume absence of distance decay for non-connected buildings and simulate expected energy expenditure and emission abatement when gas is more accessible to households. In the next two subsections we detail the econometric approach.

3.2.1. Analysis of current fuel use and gas consumption

The first task is to model the choice for building heating fuel. In Ireland, the primary fuel for residential units can be one of the following: gas, oil (incl. LPG), electricity or solid fuels (peat, coal, biomass). The response variable takes four discrete non-ordinal values. The probability of using one of these four fuels as the main central heating fuel is modelled using a multinomial logit model (MNL). Similar to Baker et al. (1989) and Braun (2010) the 'choice' of fuel in this model is understood as use or availability, rather than an actual purchase decision. In a MNL setting the probability y_i that building n is fuelled with fuel i is given by:

$$\Pr(y_i|\beta_i, x_n) = P_i = \frac{\exp\left(\beta_i' x_{in}\right)}{\sum_{i=1}^{J} \exp\left(\beta_i' x_{in}\right)}, \tag{1}$$

where X is a matrix that includes distance from the gas network and a set of building and personal characteristics and β_i is a vector of coefficients expressing the effect of the variables on the probability of fuel i connection and J is the set of fuel alternatives. Direct interpretation of the MNL parameter estimates is difficult and instead marginal effects are calculated, which show the absolute change in probability of heating fuel i in response to a change in some observed factor $z \in x_{in}$ (Train, 2009):

$$\frac{\partial P_i}{\partial z} = \beta_z P_i(1 - P_i) \tag{2}$$

Table 1: Descriptive statistics of the variables

	Proportions	Sd	min	max
Fuel Type:				
Gas	0.766	0.424	0	1
Oil	0.170	0.376	0	1
Solid Fuels	0.038	0.190	0	1
Electricity	0.027	0.161	0	1
Gas consumption:				
No kWh	0.192	0.394	0	1
<2500 kWh	0.041	0.199	0	1
2500–5000 kWh	0.055	0.228	0	1
5000-7500 kWh	0.108	0.310	0	1
7500-10000 kWh	0.142	0.349	0	1
10000-12500 kWh	0.138	0.345	0	1
12500-15000 kWh	0.110	0.313	0	1
15000-20000 kWh	0.125	0.331	0	1
>20000 kWh	0.088	0.284	0	1
Distance from Gas network:				
Less than 15m	0.548	0.498	0	1
15–20m	0.311	0.463	0	1
20–30m	0.141	0.348	0	1
Number of rooms	5.642	1.637	1	28
Year of construction:				
before 1960	0.254	0.435	0	1
1961–1990	0.399	0.489	0	1
1991–2016	0.347	0.476	0	1
House type:				
Detached houses	0.170	0.376	0	1
Semi-detached houses	0.496	0.500	0	1
Terraced houses	0.326	0.469	0	1
Flats	0.007	0.083	0	1
Tenure:				
Owner with mortgage	0.394	0.489	0	1
Outright owner	0.374	0.484	0	1
Tenants	0.132	0.338	0	1
Social housing (public)	0.095	0.293	0	1
Social housing (private)	0.006	0.078	0	1
Owners of a pc	0.742	0.438	0	1
Higher social class	0.637	0.481	0	1
Household size	2.977	1.512	1	16

The second task is to model gas consumption. As shown in Table 1 the dataset only contains consumption brackets instead of the actual kWh per building. The dependent variable is discrete and ordinal and is modelled using an ordered probit model, which assumes that energy consumption is a continuous (latent) outcome but it is only observed in a discrete form. The continuous variable y^* describing the energy consumption is modelled as follows:

$$y^* = \beta' X + \upsilon \tag{3}$$

where X is a set of building-specific variables and household characteristics, β is a set of parameters to be estimated, indicating the effect of each variable on energy consumption, υ is the error component assumed to be distributed normal (Greene, 2003). y^* is a continuous measure of the energy consumption, ranging in the interval $[-\infty, +\infty]$ (Greene and Hensher, 2009). However, y^* is only observed in the discrete form y, as follows:

$$y = \begin{cases} 0, & \text{if } -\infty < y^* \leq \tau_0 \\ 1, & \text{if } \tau_0 \leq y^* \leq \tau_1 \\ ... & \\ j, & \text{if } \tau_{j-1} \leq y^* < +\infty \end{cases} \tag{4}$$

in which $\tau_0 ... \tau_{j-1}$ are the threshold parameters to be estimated. The probability of outcome j is given by:

$$Prob[y = j|X] = F[\tau_j - \beta' X] - F[\tau_{j-1} - \beta' X], \ j = 0, 1, 2, .., J - 1. \tag{5}$$

The data on energy consumption were only available for buildings fuelled with gas and some 19 percent of the buildings had no information on consumption. To address this issue we use a modified version of the ordered probit model that accounts for sample selection of the dependent variable. Sample selection models were first proposed by Heckman (1979) for linear models and our approach represents a generalisation for ordered outcomes. Ordinarily the MNL model (1) could be used to control for sample selection, however, in practice model estimation did not converge to within normal tolerance levels. An alternative simplified approach is proposed following De Luca and Perotti (2011), where an ordered response model with sample selection is represented by a bivariate model. The latent energy consumption model is redefined for outcomes, $i = 1, 2$, and two observational rules:

$$y_i^* = \beta_i' X_i + \upsilon_i \tag{6}$$

$$S_1 = I(z_1 \gamma + \upsilon_1 > 0) \tag{7}$$

$$S_2 = \sum_{j=0}^{J} I(\tau_j < y_2^* \leq \tau_{j+1}) \quad \text{if} \quad S_1 = 1 \tag{8}$$

where $I(A)$ denotes the indicator function observing event A and where z_j is a matrix of covariates. Observability of $S_2 \in (0, 1, 2, \ldots, j)$ is confined to the subsample of observations for which $S_1 = 1$, i.e. the sub-sample of households with energy (gas) consumption data. $S_1 = 0$ occurs for households that consume other fuels as the primary heating fuel in the MNL model (i.e. oil, electricity and solid fuels). Selectivity effects operate through the correlation between the latent regression errors υ_1 and υ_2. A bivariate normal distribution is assumed for the pair of error terms (υ_1, υ_2) with mean zero and covariance Σ.

$$\Sigma = \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \tag{9}$$

The log-likelihood estimator for a random sample of N observations is the following:

$$L(\theta) = \sum_{n=1}^{N} \left\{ (1 - S_{1n}) ln\pi_{0n}(\theta) + \sum_{j=0}^{J} S_{1n} I(S_{2n=j} ln)\pi_{1jn}(\theta) \right\} \tag{10}$$

where $\theta = (\beta, \tau, \gamma, \rho)$ is the vector of parameters to be estimated and where π_{0n} and π_{1n} are respectively:

$$\begin{cases} \pi_{0n} = Pr(S_1 = 0) = 1 - \Phi(\beta X) \\ \pi_{1n} = Pr(S_1 = 1, S_2 = j) = \Phi_2(\beta X) \end{cases} \tag{11}$$

For identification reasons the selection equation must contain at least one variable that is not included in the main equation that models energy consumption (De Luca and Perotti, 2011). In estimation the distance from homes to the gas network is used to explain selection, which is not included in the equation of energy consumption because distance affects connection but not the level of consumption.

3.3. Expected change in emissions and expenditures due to increased access to gas

The first part of the analysis provides a snapshot of the variables affecting the probability of gas connection and household consumption. As shown in Table 2, using gas is less polluting per unit energy and cheaper than other fuels therefore a wider adoption of gas is an advantageous public policy. Connection to the gas network has a cost that is proportional to the distance of the building from the network. At present the cost is €249.70 for buildings within 15m of the existing network, increasing by €51.32 per metre thereafter. Our dataset reports the distance from network in three brackets (see Table 1). In the presence of distance decay, the probability of gas connection decreases at increasing distance due to higher connection cost.

Emissions factors are sourced from SEAI (2018), while fuel costs are our own estimates based on data provided by the Sustainable Energy Authority of Ireland (SEAI). Using a simulation exercise we assess how emissions and expenditures are expected to change when distance decay effects are reduced, i.e. when the cost of connection is set equivalent to the minimum cost of €249.70 for all properties, i.e. within 30 metres of the existing network. The procedure follows these four steps:

1. Estimate households' emissions and fuel expenditures
2. Estimate a model that explains the probability of gas connection due to distance decay (using modification of model (1) described below)
3. For properties not connected to the gas network estimate the effect of distance decay on gas connections as the marginal probability of being connected to the gas network at the two distance categories, 15–20m and 20–30m (with 0–15m as the reference category) conditional on building type, age and tenure.
4. Assuming constant energy demand for each household, estimate the expected changes in emissions and expenditures associated with an increased probability of switching to gas if the distance decay effects are removed (i.e. the marginal cost of gas connections beyond 15m is zero)

Table 2: Emission factors and fuel prices

Fuel	Emissions (g CO_2/kWh)	Cost €/kWh
Gas	204.7	0.0723
Oil (kerosene)	257.0	0.0658
Electricity	482.8	0.2167
Solid Fuels	357.0	0.0708

Data sourced from SEAI (2018) and directly from SEAI

For the primary census-gas dataset it is not feasible to calculate a household's total energy use, the only energy consumption data relates to gas as categorical variables, as reported in Table 1. For step 1 the HBS dataset is used to model fuel consumption as a function of household attributes, which is then employed to predict total household fuel consumption within the main census-gas dataset. The HBS dataset is a nationally representative expenditure survey. Fuel consumption (kWh) are recovered by dividing expenditures by prices from Table (2). Total energy consumption across fuels is then regressed on building attributes and household characteristics, including building age, type and size, as well as tenure and economic status. The same explanatory variables are available in the primary census-gas dataset, which permits estimation of total energy consumption and subsequently used in step 4.

To explore the association between gas connection and distance in step 2 we estimate a modified version of the MNL proposed in equation 1, in which the dependent variable is binary and equal to 1 if the primary heating fuel is gas and 0 otherwise. This modification is necessary to preclude simulation anomalies where connections to non-gas fuels increase when gas distance decay effects are removed (i.e. the marginal cost of gas connections beyond 15m is zero). With this logit, as opposed to multinomial logit model, marginal effects of distance for each household are calculated. Marginal effects show the change in probability when a discrete explanatory variable increases by one unit.

In step 3 marginal probabilities of connection to the gas network are calculated for all properties not connected to the gas network. To simulate the removal of a distance decay effect, we set the marginal probability of gas connection among households within the 15-20m and 20-30m distance brackets equivalent to the marginal probability of connection associated with properties within 0–15m of the network. In the policy simulations marginal probabilities of gas connection for each household, MP_h, are calculated conditional on distance to gas network, building type, age and tenure.

Based on each households' existing energy demand, which is calculated in step 1 from the HBS data, expected changes in emissions and expenditures allowing for the marginal probability of switching to gas (from step 3) are calculated in step 4. Emissions and expenditure across all fuels are calculated as follows:

$$Emissions = \sum_h kWh_h * factor_i \tag{12}$$

$$Expenditure = \sum_h kWh_h * p_i \tag{13}$$

where kWh_h is the imputed energy consumption for household h (from step 1), $factor_i$ is the CO_2 emissions factor for fuel type i, and p_i is the associated fuel price from Table 2. The expected change in emissions and fuel expenditure after connecting to the gas network is evaluated as:

$$\Delta emissions = \sum_h MP_h * kWh_h * (factor_{gas} - factor_i) \tag{14}$$

$$\Delta expenditure = \sum_h MP_h * kWh_h * (p_{gas} - p_i) \tag{15}$$

where in this instance $factor_i$ is the CO_2 emission factor associated with the existing heating fuel prior to switching to gas. Equations (14) and (15) are calculated across all households not currently connected to the gas network, i.e. only for households where it is possible to make a new gas network connection.

4. Results

4.1. Current fuel use and gas consumption

4.1.1. Current fuel use

Estimated parameters from the MNL model are not amenable to direct interpretation and therefore not reported. Instead Table 3 reports calculated marginal effects based on the model estimates. The figures presented show the marginal probability of a household utilising each fuel as its primary heating source associated with a change the explanatory variables in the model. The sum of marginal probabilities across fuel types for a given attribute sum to zero. The MNL model was estimated using the `mlogit` command in Stata^{TM}15. Marginal effects were calculated with the `margins` command. Where the marginal effect relates to a categorical variable the discrete first difference from the base category is reported.

The estimates show how proximity to the gas network impacts on primary heating fuel. As distance increases from the reference 0-15m category to 15-20m there is a 7.3 percentage point decrease in the probability that the property is heated by gas. The decrease is 15.1 percentage points when the distance is 20-30m. As distance to the gas network increases oil is the primary alternative fuel choice with marginal probabilities of +7.1 and +13.0 percentage points. McCoy and Curtis (2018) find that a one percent increase in average distance to the Irish gas network is associated with a 12 percentage point reduction in the proportion of gas users in an area. Estimates from these two studies are not directly comparable due to differing metrics and datasets but appear broadly consistent with each other.

The two other variables with the largest marginal effects are building age and tenure. Homes built since 1991 have a higher marginal probability of gas fuelled heating, which reflects an expansion in the use of gas in Ireland after 1980, with an annual growth in the number of gas consumers of 9% between 1980 and 2010 (Rogan et al., 2012). Property owners with a mortgage are the reference category for the tenure variable. Mortgage owners are more likely to be younger families living in more recently built properties. Outright owners (i.e. without mortgage) are 8.4 percentage points less likely than other tenure types to have a gas heating system and 6.5 percentage points more likely to have an oil-fired heating system. This tenure group has the greatest autonomy in freely selecting their heating fuel compared to renters or occupants living in different types of social or public housing. The marginal probability of consuming gas is 4 percentage points lower for families renting their home with solid fuels being the most likely alternate fuel consumed.

Among the other model variables, such as property type, size or economic status, the marginal effect estimates are relatively small in magnitude and may have less practical relevance for climate policy measures seeking to encourage the transition to less carbon intensive fossil heating fuels.

Table 3: MNL model for gas connections: Marginal effects

MNL marginal effects	Gas	Oil	Electricity	Solid fuels
Distance 15-20m	-0.073***	0.071***	0.003***	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Distance 20-30m	-0.151***	0.130***	0.012***	0.009***
	(0.002)	(0.002)	(0.001)	(0.001)
Number of rooms	0.007***	0.007***	-0.007***	-0.006***
	(0.000)	(0.000)	(0.000)	(0.000)
Year of building construction (ref. before 1960)				
Year 1961-1990	-0.020***	0.053***	-0.027***	-0.007***
	(0.002)	(0.002)	(0.001)	(0.001)
Year 1991-2016	0.228***	-0.164***	-0.060***	-0.004***
	(0.002)	(0.001)	(0.001)	(0.001)
Tenure (ref. Owners with a mortgage)				
Outright owners	-0.084***	0.065***	0.014***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Tenants	-0.040***	0.008***	-0.005***	0.038***
	(0.002)	(0.002)	(0.001)	(0.001)
Social housing (public)	0.059***	-0.084***	0.018***	0.007***
	(0.002)	(0.002)	(0.001)	(0.001)
social housing (private)	0.003	-0.060***	0.024***	0.033***
	(0.008)	(0.007)	(0.004)	(0.004)
House type (ref. Detached houses)				
Semi-detached houses	0.040***	-0.028***	-0.006***	-0.006***
	(0.002)	(0.001)	(0.001)	(0.001)
Terraces	0.064***	-0.069***	0.005***	0.001
	(0.002)	(0.002)	(0.001)	(0.001)
Flats	0.011	-0.085***	0.004	0.071***
	(0.008)	(0.008)	(0.004)	(0.004)
Upper social class	0.030***	-0.011***	-0.019***	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Household size	0.008***	-0.006***	-0.001***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Employment status (ref. employed)				
Other employment status	0.002	0.006***	-0.006***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)

Standard errors in parentheses, * p<0.1, ** p<0.05, *** p<0.01

4.1.2. Gas consumption

The ordered probit heckman selection model (equation 10) was estimated using the `heckoprobit` command in Stata^{TM}15 and the results are reported in Table 4. It is easier to interpret the results in terms of marginal effects. Table 5 displays marginal probabilities for eight categories of yearly gas consumption across different dwellings and socio-economic variables. Before proceeding we note again that the dataset does not permit calculation of income or price effects. Calculation of marginal effects associated with household or building attributes are feasible. For brevity we describe here results for the two extreme levels of yearly gas consumption <2,500 kWh and >20,000 kWh. If a household is in a higher social class, or a mortgaged owner there are similar marginal probabilities of being among the highest category gas consumer 1.8–1.9 percentage points greater than other consumers, while marginal probability of the highest consumption level is 3.2 percentage points higher for families with a retired head of household. Households in social housing have a 2.2 percentage point higher probability than others of being in the lowest consumption category. The two characteristics in Table 5 frequently associated with social disadvantage, i.e. two forms of social housing, are the attributes with the highest marginal probability estimates for the lowest levels of gas consumption. Further research is necessary to investigate if these finding are correlated with fuel poverty. On building age, newer built properties are less likely to have high levels of consumption, i.e. 12500+ kWh, relative to the reference category of pre 1960s building but more likely to have lower levels of consumption. For example, a property built in the period 1991–2016 is 4.6 percentage points more likely to have gas consumption of 5000–7500 kWh relative to a property built prior to 1960. Semi-detached, terraced properties and flats are more likely to have lower levels of gas consumption relative to the detached properties. For example, terraced properties are 7.1 percentage points more likely to have gas consumption of 5000–7500 kWh relative to a detached property.

Table 4: Gas consumption ordered probit model with Heckman correction

Variables	Consumption		Heckman selection	
	Coefficient	Std. error	Coefficient	Std. error
15–20m			-0.301***	(0.005)
20–30m			-0.608***	(0.007)
Number of rooms	0.188***	(0.001)	0.030***	(0.002)
1961–1990	-0.253***	(0.005)	-0.080***	(0.006)
1991–2016	-0.414***	(0.006)	0.999***	(0.008)
Semi-detached	-0.402***	(0.006)	0.186***	(0.006)
Terraced houses	-0.634***	(0.006)	0.271***	(0.008)
Flats	-0.493***	(0.022)	-0.387***	(0.030)
With mortgage	0.119***	(0.005)	-0.361***	(0.006)
Tenants	-0.016***	(0.006)	-0.211***	(0.008)
Social housing (public)	-0.346***	(0.006)	0.180***	(0.010)
Social housing (private)	-0.316***	(0.021)	-0.132***	(0.032)
Higher social class	0.112***	(0.004)	0.110***	(0.005)
Household size	0.134***	(0.001)	0.033***	(0.002)
Employed	-0.039***	(0.004)	0.005	(0.005)
Retired	0.186***	(0.007)	-0.057***	(0.007)
County fixed effects	Yes		Yes	
ρ	0.040*** (0.007)			
Observations	466,929			

Standard errors in parentheses, * p<0.1, ** p<0.05, *** p<0.01.

Table 5: Marginal effects of gas consumption levels across different socio-economic variables

	Gas consumption category, kWh							
	<2500	2500–5000	5000–7500	7500–10000	10000–12500	12500–15000	15000–20000	>20000
Number of Rooms	-0.012	-0.016	-0.021	-0.014	0.000	0.009	0.023	0.030
Higher social class	-0.007	-0.009	-0.013	-0.008	0.000	0.006	0.014	0.018
Employed	0.003	0.003	0.004	0.003	0.000	-0.002	-0.005	-0.006
Retired	-0.011	-0.015	-0.021	-0.015	-0.002	0.008	0.023	0.032
Tenure:								
Mortgaged	-0.008	-0.010	-0.013	-0.009	0.000	0.006	0.015	0.019
Tenants	0.001	0.001	0.002	0.001	0.000	-0.001	-0.002	-0.003
Social housing (public)	0.022	0.029	0.039	0.025	0.000	-0.017	-0.043	-0.055
Social housing (private)	0.020	0.026	0.035	0.023	0.000	-0.016	-0.039	-0.050
Building age:								
1961–1990	0.016	0.021	0.028	0.018	0.000	-0.013	-0.031	-0.040
1991–2016	0.027	0.035	0.046	0.030	0.000	-0.021	-0.051	-0.066
Building type:								
Semi-detached	0.026	0.034	0.045	0.029	0.000	-0.020	-0.050	-0.064
Terraced	0.041	0.053	0.071	0.046	0.001	-0.032	-0.079	-0.101
Flats	0.032	0.041	0.055	0.036	0.000	-0.025	-0.061	-0.079

The majority of estimates are statistically significant at 1 percent level, most of the remainder at 5 per cent level, with just a few at 10 per cent level. All lower significance levels occur for estimates related to the 10000–12500 kWh category.

4.2. Expected change in emissions and expenditures due to increased access to gas

The probability of connection to the gas network declines as distance to the gas network increases, as illustrated earlier. This section presents the results of the simulation analysis investigating the impact on residential emissions and expenditures if the gas connection distance decay effect is eliminated, as described in section 3.3. In practice such a scenario could arise if the marginal cost of gas connections beyond 15m is set at zero and a flat connection fee, currently €249.70, applies to all new connections up to 30 metres.

With the removal of the distance decay effect new gas connections are anticipated. The magnitude of the distance decay effect was reported in section 4.1.1; as distance increases from the reference 0-15m category to 15-20m there is a 7.3 percentage point decrease in the probability that the property is heated by gas and a 15.1 percentage point decrease when the distance is 20-30m. As noted earlier, the simulation results are based on a logit, as opposed to a multinomial logit model, to avoid irrational outcomes where connections to non-gas fuels increase when gas distance decay effects are removed. The estimated distance decay effects from the logit model at 7.3 and 15.7 are similar to the MNL estimates. The marginal probability of a gas connection also varies depending on other building attributes and household characteristics. For the simulation analysis the marginal probability of a gas connection is calculated for 36 separate combinations of building attributes and household characteristics across building type, building age, tenure and distance to the gas network. These variables were selected because they may be useful as potential hooks for policy measures. For example, potential policy incentives could target specific house types or building ages. Results for just 4 combinations are reported in Table 6, representing the estimated minimum and maximum marginal probabilities within the 15–20m and 20–30m distance categories. Accordingly, the estimates in Table 6 bracket the range of marginal probability estimates of a gas network connection associated with these household/property types ceasing to be impacted by network distance effects. For households/buildings within 15–20 metres of the gas network, the marginal probability of a gas connection is 2.3–11.2 percentage points less compared to households within 0–15 metres of the network. The corresponding figures for households within 20–30 metres of the network are 5.3–22.1 percentage points. The category of buildings/households with the highest magnitude marginal effects are detached houses, built in the 1960–1990 period, and which are owned outright. Housing developments with these characteristics are likely to have the highest probability of switching to gas if the cost of gas connection is a flat fee.

Table 6: Marginal effect of network distance conditional on building and household attributes

Distance	Year built	House type	Tenure	Marginal probability	Std error.
15-20 m	1960–1990	Detached	Owned outright	-0.112***	0.002
15-20 m	Post 1990	Terraced	Mortgaged	-0.023***	0.001
20-30 m	1960–1990	Detached	Owned outright	-0.221***	0.002
20-30 m	Post 1990	Terraced	Mortgaged	-0.053***	0.001

Marginal effects were calculated with the `margins` command in Stata™ and standard errors calculated by delta method. * p<0.1, ** p<0.05, *** p<0.01

If a flat connection fee is extended to cover all properties up to 30 metres one would expect new gas connections in the 15–30 metre range. The next set of results relates to expected change in emissions and expenditures if such a policy were implemented. In total there are 69,000 unconnected properties within 15–30 metres of the gas network. We calculate the expected change in emissions and expenditure as outlined in equations (14) and (15). Switching heating fuel to gas brings environmental benefits, as emissions are expected to decrease by 3.9% across all un-connected households within 15–30 metres of the gas network. The corresponding reduction in heating fuel expenditure is 1.5%. The results are reported in Table 7, which also includes the results by distance to network. The expected number of properties making a new gas connection is just above 9,000, or 13% of potential new connections.

There are revenue implications for the gas network operator but the reduction in emissions also has value. The loss of connection fees to the gas network operator is estimated at €3.3 million but actual connection costs may be different. The reduction in emissions does not have a direct financial value, as the emissions from the residential sector are not within a traded carbon market, such as the EU's Emissions Trading Scheme. But emission reductions have value to the government, which has legally binding emission reduction targets within the EU's burden sharing agreement. To calculate the value of carbon reduction savings we assume that the emissions reductions persist over time and we use a 4% discount rate, which is the standard discount rate to be used in cost-benefit and cost-effectiveness analyses for Irish public sector projects.[1] For the value of carbon we use the shadow value of carbon from the Irish public spending code, which is €39/tCO_2 in 2021 rising to €105 in 2030 and to €163 by 2040. The estimated value of discounted emissions savings is €9m over a ten year time horizon to 2030 or €21m over a twenty year horizon to 2040.

4.3. Distributional effects of increased access to gas

Understanding the distributional effect of environmental policies is important to protect against inequalities for the more vulnerable in society. For example, carbon taxes impose a heavier burden on poorer households so implementation of new carbon taxes is often combined with other social welfare measures (Klenert et al., 2018; Flues and Thomas, 2015; Tovar Reaños and Wölfing, 2018). Understanding the distributional effects of a measure to improve access to the gas network helps inform public funding decisions

[1] https://www.gov.ie/en/policy-information/1a0dcb-project-discount-inflation-rates/

Table 7: Expected change in emissions, fuel expenditure and marginal cost needed for the connection (of all unconnected dwellings located within 15–30m of the gas network)

Description :	15-20m	20-30m	Total
Δemissions, %	-2.7	-5.4	-3.9
Δexpenditure, %	-1.2	-2.0	-1.5
Number of dwellings unconnected to the gas network	40,733	28,706	69,439
Estimated number of new connections	3,864	5,523	9,387
Emissions savings, tCO_2	6,886	10,188	17,073
Estimated connection revenue foregone, €m	0.5	2.8	3.3

Table 8: Simulation outputs by socio-economic group

Socio-economic group Description	Label	Unconnected households within 15–30m of gas network	Change in CO_2 emissions	Change in expenditure	Average change in expenditure, €/yr
Employers & managers	A	14%	-3.5%	-0.5%	-10
Professionals	B+C	19%	-3.6%	-0.5%	-9
Manual/non-manual labour	D+E	31%	-3.9%	-1.6%	-29
Semi-skilled/unskilled	F+G	10%	-4.2%	-2.8%	-50
Other	Other	26%	-4.1%	-2.2%	-43
Total		100%	-3.9%	-1.5%	-28

for such a policy. The data available does not include information on income but socio-economic group is is a possible proxy. Table 8 reports the simulation results for the main socio-economic groups. Of the unconnected households within 15–30m of the gas network the largest share, at 31%, are attributed as manual and non-manual labourers. The change emissions and expenditure for this group closely matches all unconnected households within 15–30m of the gas network. Among unconnected households across the socio-economic groups 74–86% of households' existing heating fuel is oil, 6–8% solid fuels, and the remainder electricity. Semi and unskilled workers would experience the largest reductions in both emissions and expenditure, of 4.2% and 2.8% respectively. Whereas the more affluent socio-economic groups comprising professionals, employers, and managers would experience just a 0.5% reduction in expenditure associated with a switch to gas (and assuming unchanged kWh energy consumption). The simulated absolute change in expenditure varies between €9–50 per annum per household. A €50 reduction in heating fuel expenditure for Semi-skilled/unskilled households in some instances may represent substantial saving. Without income data there are no conclusive results with respect to impacts on fuel poverty or the alleviation of distributional inequalities but nominally the measure appears progressive with respect to distributional impacts.

5. Discussion

Reducing energy demand of existing dwellings through energy efficiency improvements is a common strategy for emission reductions across many countries. Increasing gas access is not usually advocated as a strategy to achieve emission reduction targets but the analysis here clearly shows that there is scope for achieving emissions reductions through a policy that advocates transition from more carbon intensive heating fuels such as oil to fossil gas. At a national scale the magnitude of emissions reductions is relatively small but nonetheless contributes to challenging national targets. Switching to fossil gas can be considered as an intermediate step, as in the longer term renewable biomethane can be used as a substitute for fossil gas. For instance, SEAI (2017) suggests Ireland has the largest potential of biogas production per capita within the EU while Rajendran et al. (2019) recommend the introduction of incentives for biomethane production in Ireland and its injection into the gas network to seamlessly integrate renewable gas into heating.

The fuel type used in residential buildings is strongly associated with building age and type among other factors, as was demonstrated in the MNL model estimates. Switching to a lower or zero carbon fuel is not a simple choice and often requires substantial investment in technology. In the case of gas, connection fees appear to be an additional barrier, as demonstrated by the estimated marginal probabilities associated with network distance of between 5 and 22 percentage points. The key price variable is the connection cost, which is a function of distance to the network (McCoy and Curtis, 2018). While the distance to the network is included in our model, we acknowledge that while projected new connections are based on a model of socio-demographic and building characteristics, income and price effects are excluded due to absence of data. In the scenario examined, where the flat rate connection fee is extended to all properties within 30 metres, the analysis estimates that up to 13% of potentially available properties would respond to the improved connection incentive, though the level of connection is likely to differ substantially based on property and household characteristics. The impact of distance on connection is particularly acute among among owner-occupiers living in detached properties, with the marginal probability of connection declining by half as distance to network increases from 15–20m to 20–30m. Financial or budget constraints are among the key barriers to investment in energy retrofits, which may affect new gas conversion rates in practice, as will other common barriers such as those related to information or disruption (Sorrell et al., 2004; Caird et al., 2008; Mills and Schleich, 2012; Achtnicht and Madlener, 2014). In practice the level of new connections following such a policy is likely to be less than 13% when the impact of barriers is incorporated.

Climate policies such as carbon taxation are generally regressive (Klenert et al., 2018; Flues and Thomas, 2015; Tovar Reaños and Wölfing, 2018) and are often combined with revenue hypothecation to compensate those facing the most significant associated burden. Unusually, a policy support to encourage fuel switching to gas may be progressive, as the reduction in fuel expenditure disproportionately favours socio-economic groups that are more likely to be disadvantaged. Nominally, in this instance a single measure is achieving two public policy goals of reducing greenhouse gas emissions and tackling income inequality. In practice the switching to a gas based heating system requires household investment, for example in gas boilers and associated plumbing, which may be barrier to those on low incomes. Therefore, the extent to which a policy measure supporting switching to gas can contribute to tackling both policy goals is subject to future research. The distributional impacts of carbon taxation have been widely considered (e.g. Callan et al., 2009; Liang and Wei, 2012; Feng et al., 2010) but there is scope for examination of other climate-energy policy measures .

From a simple cost-benefit perspective the cost of the policy measure in terms of revenue foregone is easily offset by the value of avoided emissions and a case to implement such a policy could be argued. In practice, however, this is a case of split incentives. The costs of the policy support are borne solely by the gas network operator. Households switching to gas also incur costs (e.g. installation of new heating equipment) but benefit from reduced fuel costs. Neither the gas network operator nor households benefit financially from the reduction in emissions. The State is the sole beneficiary of reduced emissions in terms of its compliance with legally binding emissions reduction targets. A solution to this split incentive problem is to devise an incentive to all parties such that the value of the CO_2 savings are shared.

6. Conclusions

The paper examines non-price drivers associated with residential fuel choice, with special focus on gas network connection and consumption. Similar to earlier research we find that a range of building attributes and household characteristics are associated with fuel choice. Of particular policy relevance we find substantial distance decay effects with respect to gas network connection within relatively close proximity to the network, meaning that properties further distant from the gas network are less likely to be gas customers. Network connection fees proportional to distance appear to be a barrier to gas as a home heating fuel, though there may be other compounding factors such as additional installation costs. Switching from coal or oil to natural gas for heating purposes can yield CO_2 emissions reductions and the distance decay effect can be exploited to incentivise switching to natural gas and achieve emissions savings. Simulating a new connections policy that institutes a flat fee for all properties within 30m of the network, i.e. eliminate the cause of the distance decay effect, we project that up to 14% of eligible unconnected properties may respond to the incentive. In practice, the level of new connections is likely to be lower, as the analysis was unable to incorporate the impact of several well known barriers to energy retrofits. However, the research shows substantial variation in the probability of connection based on property age and type, tenure, and distance to the network. In specific areas the potential for new connections is relatively high, whereas in other areas it is quite low. The aggregate results for the simulation are a 3.9% reduction in CO_2 emissions compared to a baseline of heating related emissions from unconnected properties within 15–30m of the network. Aggregate fuel expenditure declines by 1.5%, though the expenditure reductions are disproportionately in favour of manual and unskilled workers, cohorts that are often associated with low incomes. The implementation cost of a flat-rate connection fee in terms of revenue foregone is relatively modest with respect to the value of emissions avoided but the measure is subject to split incentives. While nominally counter-intuitive, greenhouse gas emissions from the residential sector could be reduced by devising a programme to incentivise connection to the natural gas network.

References

Achtnicht, M. and Madlener, R. (2014). Factors influencing german house owners' preferences on energy retrofits. *Energy Policy*, 68:254–263. https://doi.org/10.1016/j.enpol.2014.01.006.

Allcott, H. (2011). Social norms and energy conservation. *Journal of Public Economics*, 95(9-10):1082–1095. https://doi.org/10.1016/j.jpubeco.2011.03.003.

Allcott, H. and Rogers, T. (2014). The short-run and long-run effects of behavioral interventions: Experimental evidence from energy conservation. *American Economic Review*, 104(10):3003–37. https://doi.org/10.1257/aer.104.10.3003.

Arabatzis, G. and Malesios, C. (2011). An econometric analysis of residential consumption of fuelwood in a mountainous prefecture of Northern Greece. *Energy policy*, 39(12):8088–8097. https://doi.org/10.1016/j.enpol.2011.10.003.

Baker, P., Blundell, R., and Micklewright, J. (1989). Modelling household energy expenditures using micro-data. *The Economic Journal*, 99(397):720–738. https://doi.org/10.2307/2233767.

Blattenberger, G. R., Taylor, L. D., and Rennhack, R. K. (1983). Natural gas availability and the residential demand for energy. *The Energy Journal*, 4(1):23–45. https://www.jstor.org/stable/41321584.

Braun, F. G. (2010). Determinants of households' space heating type: A discrete choice analysis for German households. *Energy Policy*, 38(10):5493–5503. https://doi.org/10.1016

Caird, S., Roy, R., and Herring, H. (2008). Improving the energy performance of uk households: Results from surveys of consumer adoption and use of low-and zero-carbon technologies. *Energy Efficiency*, 1(2):149. https://doi.org/10.1007/s12053-008-9013-y.

Callan, T., Lyons, S., Scott, S., Tol, R. S., and Verde, S. (2009). The distributional implications of a carbon tax in Ireland. *Energy Policy*, 37(2):407–412. https://doi.org/10.1016/j.enpol.2008.08.034.

Cebula, R. J. (2012). US residential electricity consumption: the effect of states' pursuit of energy efficiency policies. *Applied Economics Letters*, 19(15):1499–1503. https://doi.org/10.1080/13504851.2011.637884.

Choi, A. S. (2013). Nonmarket values of major resources in the korean dmz areas: A test of distance decay. *Ecological Economics*, 88:97–107.

Couture, S., Garcia, S., and Reynaud, A. (2012). Household energy choices and fuelwood consumption: An econometric approach using French data. *Energy Economics*, 34(6):1972–1981. https://doi.org/10.1016

Curtis, J., McCoy, D., and Aravena, C. (2018). Heating system upgrades: The role of knowledge, socio-demographics, building attributes and energy infrastructure. *Energy Policy*, 120:183–196. https://doi.org/10.1016/j.enpol.2018.05.036.

De Luca, G. and Perotti, V. (2011). Estimation of ordered response models with sample selection. *The Stata Journal*, 11(2):213–239. https://journals.sagepub.com/doi/pdf/10.1177/1536867X1101100204.

Decker, T. and Menrad, K. (2015). House owners' perceptions and factors influencing their choice of specific heating systems in Germany. *Energy Policy*, 85:150–161. https://doi.org/10.1016/j.enpol.2015.06.004.

Delmas, M. A., Fischlein, M., and Asensio, O. I. (2013). Information strategies and energy conservation behavior: A meta-analysis of experimental studies from 1975 to 2012. *Energy Policy*, 61:729–739. https://doi.org/10.1016/j.enpol.2013.05.109.

Dergiades, T. and Tsoulfidis, L. (2008). Estimating residential demand for electricity in the United States, 1965–2006. *Energy Economics*, 30(5):2722–2730. https://doi.org/10.1016/j.eneco.2008.05.005.

European Commission (2011a). *Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions: Energy efficiency plan 2011*. COM(2011) 109 final. European Commission. https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=COM:2011:0109:FIN:EN:PDF.

European Commission (2011b). *Communication From The Commission To The European Parliament, The Council, The European Economic And Social Committee And The Committee Of The Regions: Energy Roadmap 2050*. COM(2011) 885 final. European Commission. http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=COM:2011:0885:FIN:EN:PDF.

Feng, K., Hubacek, K., Guan, D., Contestabile, M., Minx, J., and Barrett, J. (2010). Distributional effects of climate change taxation: the case of the uk. https://doi.org/10.1021/es902974g.

Filippini, M. (1999). Swiss residential demand for electricity. *Applied Economics Letters*, 6(8):533–538. https://doi.org/10.1080/135048599352880.

Filippini, M. and Hunt, L. C. (2012). US residential energy demand and energy efficiency: A stochastic demand frontier approach. *Energy Economics*, 34(5):1484–1491. https://doi.org/10.1016/j.eneco.2012.06.013.

Finger, M. (1994). From knowledge to action? exploring the relationships between environmental experiences, learning, and behavior. *Journal of social issues*, 50(3):141–160. https://doi.org/10.1111/j.1540-4560.1994.tb02424.x.

Flues, F. and Thomas, A. (2015). The distributional effects of energy taxes. OECD Taxation Working Papers 23, OECD Publishing.

Frederiks, E. R., Stenner, K., and Hobman, E. V. (2015). Household energy use: Applying behavioural economics to understand consumer decision-making and behaviour. *Renewable and Sustainable Energy Reviews*, 41:1385–1394. https://doi.org/10.1016/j.rser.2014.09.026.

Fu, M., Kelly, J. A., and Clinch, J. P. (2014). Residential solid fuel use: Modelling the impacts and policy implications of natural resource access, temperature, income, gas infrastructure and government regulation. *Applied Geography*, 52:1–13. https://doi.org/10.1016/j.apgeog.2014.04.007.

Garbacz, C. (1984). Residential demand for liquid petroleum gas. *Economics Letters*, 15(3-4):345–349. https://doi.org/10.1016/0165-1765(84)90123-X.

Garbacz, C. (1985). Residential fuel oil demand: a micro-based national model. *Applied Economics*, 17(4):669–674. https://doi.org/10.1080/758534697.

Greene, W. H. (2003). *Econometric Analysis*. Pearson Education India.

Greene, W. H. and Hensher, D. A. (2009). *Modeling ordered choices: A Primer*. Cambridge university press, Cambridge, UK. https://doi.org/10.1037/0021-9010.91.1.97.

Haas, R. and Schipper, L. (1998). Residential energy demand in OECD-countries and the role of irreversible efficiency improvements. *Energy Economics*, 20(4):421–442. https://doi.org/10.1016/S0140-9883(98)00003-6.

Halvorsen, R. (1975). Residential demand for electric energy. *The Review of Economics and Statistics*, 57(1):12–18. http://dx.doi.org/10.2307/1937858.

Harold, J., Lyons, S., and Cullinan, J. (2015). The determinants of residential gas demand in Ireland. *Energy Economics*, 51:475–483. http://dx.doi.org/10.1016/j.eneco.2015.08.015.

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica: Journal of the econometric society*, pages 153–161.

Holtedahl, P. and Joutz, F. L. (2004). Residential electricity demand in Taiwan. *Energy economics*, 26(2):201–224. https://doi.org/10.1016/j.eneco.2003.11.001.

Hosier, R. H. and Dowd, J. (1987). Household fuel choice in Zimbabwe: An empirical test of the energy ladder hypothesis. *Resources and Energy*, 9(4):347–361.

Houthakker, H. S. (1951). Some calculations on electricity consumption in Great Britain. *Journal of the Royal Statistical Society*, 114(3):359–371. http://dx.doi.org/10.2307/2980781.

Kayacan, B., Ucal, M. Ş., Öztürk, A., Balı, R., Koçer, S., and Kaplan, E. (2012). A primary econometric approach to modeling and forecasting the demand for fuelwood in Turkey. *Journal of Food, Agriculture & Environment*, 10(3&4):934–937.

Klenert, D., Mattauch, L., Combet, E., Edenhofer, O., Hepburn, C., Rafaty, R., and Stern, N. (2018). Making carbon pricing work for citizens. *Nature Climate Change*, 8(8):669–677.

Knapp, L. and Ladenburg, J. (2015). How spatial relationships influence economic preferences for wind power—a review. *Energies*, 8(6):6177–6201.

Krishnamurthy, C. K. B. and Kriström, B. (2015). A cross-country analysis of residential electricity demand in 11 OECD-countries. *Resource and Energy Economics*, 39:68–88. https://doi.org/10.1016/j.reseneeco.2014.12.002.

Labandeira, X., Labeaga, J. M., and López-Otero, X. (2017). A meta-analysis on the price elasticity of energy demand. *Energy Policy*, 102:549–568. https://doi.org/10.1016/j.enpol.2017.01.002.

Laureti, T. and Secondi, L. (2012). Determinants of households' space heating type and expenditures in Italy. *International Journal of Environmental Research*, 6(4):1025–1038. https://doi.org/10.22059/IJER.2012.573.

Liang, Q.-M. and Wei, Y.-M. (2012). Distributional impacts of taxing carbon in china: results from the ceepa model. *Applied Energy*, 92:545–551. https://doi.org/10.1016/j.apenergy.2011.10.036.

Lillemo, S. C., Alfnes, F., Halvorsen, B., and Wik, M. (2013). Households' heating investments: the effect of motives and attitudes on choice of equipment. *Biomass and bioenergy*, 57:4–12. https://doi.org/10.1016/j.biombioe.2013.01.027.

Lillemo, S. C. and Halvorsen, B. (2013). The impact of lifestyle and attitudes on residential firewood demand in Norway. *Biomass and bioenergy*, 57:13–21. https://doi.org/10.1016/j.biombioe.2013.01.024.

Mansur, E. T., Mendelsohn, R., and Morrison, W. (2008). Climate change adaptation: A study of fuel choice and consumption in the US energy sector. *Journal of Environmental Economics and Management*, 55(2):175–193. https://doi.org/10.1016/j.jeem.2007.10.001.

McCoy, D. and Curtis, J. (2018). Exploring the spatial and temporal determinants of gas central heating adoption. *Resource and Energy Economics*. https://doi.org/10.1016/j.reseneeco.2017.12.004.

Meier, H. and Rehdanz, K. (2010). Determinants of residential space heating expenditures in Great Britain. *Energy Economics*, 32(5):949–959. https://doi.org/10.1016/j.eneco.2009.11.008.

Michelsen, C. C. and Madlener, R. (2012). Homeowners' preferences for adopting innovative residential heating systems: A discrete choice analysis for Germany. *Energy Economics*, 34(5):1271–1283. https://doi.org/10.1016/j.eneco.2012.06.009.

Michelsen, C. C. and Madlener, R. (2016). Switching from fossil fuel to renewables in residential heating systems: An empirical study of homeowners' decisions in Germany. *Energy Policy*, 89:95–105. https://doi.org/10.1016/j.enpol.2015.11.018.

Mills, B. and Schleich, J. (2012). Residential energy-efficient technology adoption, energy conservation, knowledge, and attitudes: An analysis of European countries. *Energy Policy*, 49:616–628. https://doi.org/10.1016/j.enpol.2012.07.008.

Nekola, J. C. and White, P. S. (1999). The distance decay of similarity in biogeography and ecology. *Journal of Biogeography*, 26(4):867–878.

Nesbakken, R. (2001). Energy consumption for space heating: a discrete–continuous approach. *Scandinavian Journal of Economics*, 103(1):165–184. https://doi.org/10.1111/1467-9442.00236.

Okajima, S. and Okajima, H. (2013). Estimation of Japanese price elasticities of residential electricity demand, 1990–2007. *Energy Economics*, 40:433–440. https://doi.org/10.1016/j.eneco.2013.07.026.

Özcan, K. M., Gülay, E., and Üçdoğruk, Ş. (2013). Economic and demographic determinants of household energy use in Turkey. *Energy Policy*, 60:550–557. https://doi.org/10.1016/j.enpol.2013.05.046.

Pindyck, R. S. (1980). International comparisons of the residential demand for energy. *European Economic Review*, 13(1):1–24. https://doi.org/10.1016/0014-2921(80)90044-6.

Poortinga, W., Steg, L., and Vlek, C. (2004). Values, environmental concern, and environmental behavior: A study into household energy use. *Environment and behavior*, 36(1):70–93. https://doi.org/10.1177/0013916503251466.

Rajendran, K., Ó Gallachóir, B., and Murphy, J. D. (2019). The role of incentivising biomethane in Ireland using anaerobic digestion. *Environmental Protection Agency (EPA) Research Report 279*, 2016-RE-DS-6. http://www.epa.ie/pubs/reports/research/waste/Research_Report_279.pdf.

Rogan, F., Cahill, C. J., and Ó Gallachóir, B. P. (2012). Decomposition analysis of gas consumption in the residential sector in Ireland. *Energy Policy*, 42:19–36. http://dx.doi.org/10.1016/j.enpol.2011.10.059.

Schultz, P. W. and Zelezny, L. (1999). Values as predictors of environmental attitudes: Evidence for consistency across 14 countries. *Journal of environmental psychology*, 19(3):255–265. https://doi.org/10.1006/jevp.1999.0129.

SEAI (2017). *Assessment of Cost and Benefits of Biogas and Biomethane in Ireland*. Sustainable Energy Authority of Ireland (SEAI), Dublin. https://www.seai.ie/publications/Assessment-of-Cost-and-Benefits-of-Biogas-and-Biomethane-in-Ireland.pdf.

SEAI (2018). *Energy-related CO_2 emissions in Ireland 2005–2016*. Sustainable Energy Authority Ireland. https://www.seai.ie/publications/Energy-Emissions-2017-Final.pdf.

Sorrell, S., O'Malley, E., Schleich, J., and Scott, S. (2004). *The Economics of Energy Efficiency: Barriers to Cost-effective Investment*. Edward Elgar.

Tovar Reaños, M. A. and Wölfing, N. M. (2018). Household energy prices and inequality: Evidence from german microdata based on the easi demand system. *Energy Economics*, 70:84–97.

Train, K. E. (2009). *Discrete Choice Methods with Simulation*. Cambridge University Press, New York, USA.

U.S. Department of Energy (2012). *Buildings and Energy Data Book 2011*. Department of Energy, United States of America. https://catalog.data.gov/dataset/buildings-energy-data-book-6d4d2.

Wadud, Z., Noland, R. B., and Graham, D. J. (2010). A semiparametric model of household gasoline demand. *Energy Economics*, 32(1):93–101. https://doi.org/10.1016/j.eneco.2009.06.009.