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Exploring the spatial and temporal determinants of gas central heating adoption

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ABSTRACT

In order to better understand the potential for both policy and technological improvements to aid carbon abatement, long-term historical information on the time-path of transition from more traditional to cleaner fuels is useful. This is a relatively understudied element of the fuel switching literature in both developed and emerging economies. This research adds to this literature by examining the adoption time-path of network gas as a heating fuel. We merge a unique dataset on gas network roll-out over time, with other geo-coded data and employ an instrumental variables technique in order to simultaneously model supply and demand. Results indicate a non-linear relationship between the proportion of households using gas as their primary means of central heating and the length of time the network has been in place in each area. Proximity to the gas network, peat bogs, and areas which have banned the consumption of bituminous coal also affect gas connections. Variations in socioeconomic and dwelling characteristics at area level can also help explain connections to the gas network. A better understanding of this variation is crucial in designing targeted policies and can aid network expansion decisions.

1. Introduction

Policy interest in residential fuel choice and consumption has a long history (e.g. Halvorsen, 1975; Houthakker, 1951). In recent years policy focus has centred on associated health outcomes and economic growth in developing countries and more generally on the contribution to greenhouse gas emissions. With approximately one quarter of the EU's total primary energy requirement in the residential buildings,[1] the sector is a focal point given the EU's ambition to reduce greenhouse gas emissions (European Commission, 2014). Fuel switching away from carbon intensive fuels, such as peat and coal to less carbon intensive fuels, such as gas or renewables is one way the residential sector can reduce emissions yet satisfy energy service demands.

A body of research within development economics focuses on the so-called 'energy ladder', in which households transition from traditional heating and cooking fuels, such as biomass or wood, to fuels such as gas or electricity as their income levels increase (Hosier and Dowd, 1987). As households will continue to use traditional fuels such as firewood along with modern fuels, switching back in response to relative prices and other factors (Wickramasinghe, 2011; Van der Kroon et al., 2013)

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[1] See http://ec.europa.eu/eurostat/web/energy/data/energy-balances for details.

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some have argued that a multiple fuel model is more appropriate (Masera et al., 2000). Among the key determinants of fuel choice among households in developing countries are fuel prices, income, and education, as well as security of supply considerations for fuels such as gas and electricity (Alem et al., 2016; Behera et al., 2016; Mensah and Adu, 2015; Zhang and Hassen, 2017).

Residential fuel choice[2] and fuel switching, are also a research focus in developed economies. For example, there has been a particular interest in recent years into the decision to adopt renewable or more efficient residential heating systems (Mahapatra and Gustavsson, 2008; Sopha and Klockner, 2011; Michelsen and Madlener, 2012). Across numerous studies and countries there is a general consensus on the range of factors which determine residential fuel choice. These are described in detail in Section 2. Our research adds to both this literature and the literature examining the acquisition of energy using assets.[3]

Our focus in this paper is on the adoption of gas central heating in Ireland. Ireland provides a very interesting lens through which to examine the diffusion of an energy-using asset over time. A cultural legacy of solid fuel usage, driven by plentiful local endowments of peat, created a reluctance to switch to more modern heating systems. This contrasts with a strong policy push in recent years to encourage greater usage of renewable energy, and recent legislation prohibiting the sale and use of bituminous coal for domestic heating in urban areas. Access to network gas has been available in some locations in Ireland for more than century, however, network connections can still be relatively low in some locations adjacent to the gas network.

We are particularly concerned with understanding more about the adoption time-path of network gas as a domestic heating fuel. There may be several reasons why a time-lag in the adoption of more efficient heating methods, once available, exists. The range of factors include financial barriers, spatial proximity to alternative energy sources, cultural legacies resulting in preferences for certain fuels, misinformation or a lack of information on alternatives, or uncertainty about future energy prices. Heterogeneity of preferences in the population can also explain variations in the timing of adoption, even in cases where the new technology is qualitatively better than the existing one.

The time-lag in adoption is a relatively under researched aspect of fuel switching, which generally consider network access as a binary variable at a point in time. Our focus is enabled by access to a rare dataset comprising detailed information on the location and timing of the expansion of each individual segment of the of the Irish gas network over 100 years. This is linked to information on the location of every residential dwelling in the country and combined with spatial cross-sectional data on area-level fuel choice along with information on dwelling attributes and the socio-demographic characteristics of households. Suppliers are likely to extend the gas network to areas of high density, or those with a higher probability of adoption, and only those households in close proximity to the gas infrastructure can adopt. Not taking account of this could potentially bias our estimates. To account for this simultaneity, we estimate a two-stage least squares specification, allowing us to identify the time-path of network roll-out in the second-stage gas adoption equation.

Results indicate a non-linear relationship between the length of time the network has been in place and the proportion of gas users in each area. Each year the network has been in place is associated with a 3 percentage point increase in gas connections on average, and this effect decreases over time. Variation in distance to the network is a significant determinant of connections, even for areas in close proximity to the network. Proximity to peat sources, such as bogs is negatively associated with gas connections, while a ban on the sale and burning of bituminous coal which was in place in various urban locations in Ireland in 2011, is positively associated with gas adoption. Our econometric approach allows us to also provide some scenario analysis which simulates gas network expansions yet to be undertaken and the potential impact of these on uptake and the associated changes in CO_2 emissions.

The layout of the remainder of the paper is as follows. The next section places our research in an international context. Following this in Section 3 we provide some background on the historical development of residential fuel usage in Ireland, including the growth in network gas usage. Section 4 outlines the model and estimation strategy we propose, which is followed by an overview of the data used. Estimation results and a scenario analysis simulating gas network expansion are presented in Sections 6 and 7. Section 8 outlines a range of robustness checks undertaken. Section 9 concludes and provides some insights for policy.

2. Related literature

As mentioned above, of primary relevance to this research is the literature concerning fuel choice and switching. In addition to this, we also draw on other research examining the acquisition of energy using assets. With regard to the former, the key determinants are considered in turn in the following paragraphs.

Building attributes, particularly property age and type affect fuel choice. Michelsen and Madlener (2016) find that older homes are less likely to switch to renewable heating systems, possibly reflecting unsuitable existing heating infrastructure. The inhabitants of older properties are more likely to use oil, firewood and coal, whereas those in more recently built properties are more likely to use gas or heat pumps (Laureti and Secondi, 2012; Michelsen and Madlener, 2012), though

[2] The term 'residential fuel choice' is used interchangeably with 'residential heating system', as some of the literature focuses on particular heating technologies, e.g. heat pumps, rather than the fuel types.

[3] This is also described in Section 2. For a prominent recent example see Gertler et al. (2016).

Lillemo et al. (2013) find that dwelling size and type impact on heating system choice but not the property's age. Larger sized properties are more likely to use gas for heating instead of solid fuels (Lillemo et al., 2013; Michelsen and Madlener, 2012). Determinants of fuel or heating systems in newly built properties generally differs to that for the existing housing stock. Michelsen and Madlener (2012) conclude that choice of a heating system in newly built homes is highly influenced by the occupants' environmental preferences.

Occupants' socio-economic characteristics also impact on fuel choice, with income, age, education and economic status being particularly relevant. A number of studies find that lower incomes are associated with oil and solid fuels, which are more emissions intensive (Fu et al., 2014; Laureti and Secondi, 2012; Özcan et al., 2013) though there are many other studies that find only a minor income effect or none (e.g. Braun, 2010; Lillemo et al., 2013; Couture et al., 2012). The effects of higher education and economic status on fuel choice are generally similar to those associated with income. In the case of age 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. On the contrary, Decker and Menrad (2015) find that neither age, education nor income are important variables in explaining choice of residential heating systems in Germany.

Inertia, peer effects and motivational impacts have also been found to impact on fuel choice. Households are often reluctant to adopt more energy efficient options, even if it is financially advantageous for them to do so. This energy-efficiency gap also characterises the reluctance to adopt other types of energy efficient appliances that offer seemingly positive benefit (Allcott and Greenstone, 2012; Blumstein et al., 1980; Jaffe and Stavins, 1994). The influence of peers is an important determinant of decisions relating to heating system choice (Decker and Menrad, 2015; Michelsen and Madlener, 2013). Other important motivational factors include attitude to particular heating systems or fuels, personal comfort and external threats, the later of which refers to either an apprehension relating to dependency on fossil fuels or climate related environmental concerns.

Regional or cultural differences, including the local availability of particular fuels such as firewood, can impact on fuel choice (Braun, 2010; Fu et al., 2014; Laureti and Secondi, 2012). While weather is frequently included as a covariate in modelling energy consumption it also has an impact on fuel choice, similar to a regional effect. In a number of cases 30-year mean weather data is found to have a strong influence on fuel choice, with higher temperature locations less likely to use oil or solid fuels (Fu et al., 2014; Mansur et al., 2008).

Fuel prices and heating system capital costs have substantial impacts on home heating decisions. The capital cost of heating system equipment can act as a barrier in fuel choice decisions due to budget constraints, however, it is difficult to capture empirical evidence in revealed behaviour data. Michelsen and Madlener (2016) find that capital costs rather than fuel prices are an important motivational factor in such decisions. In a number of stated preference studies capital costs are an important attribute or potential barrier associated with residential heating system choice decisions (Rouvinen and Matero, 2013; Scarpa and Willis, 2010). There are relatively high implicit discount rates associated with electricity and oil based heating systems compared to district heating, geothermal or wood-based systems. Fuel prices are certainly important considerations in household fuel choice decisions in developing countries (Alem et al., 2016; Mensah and Adu, 2015; Zhang and Hassen, 2017) but there is mixed evidence in developed countries. In the stated-preference studies fuel prices have a significant impact (Rouvinen and Matero, 2013; Scarpa and Willis, 2010) but only a small number of other empirical studies include fuel prices as a potential determinant of fuel choice. Mansur et al. (2008) find clear own-price and cross-price effects on fuel choice decisions, while Couture et al. (2012) find a price effect associated with firewood, the only fuel price they consider. Numerous papers examining determinants of household fuel choice do not include fuel prices as explanatory variables, though that may reflect difficulty of acquiring such information for cross-sectional datasets (e.g. Fu et al., 2014; Michelsen and Madlener, 2012; Özcan et al., 2013; Laureti and Secondi, 2012).

Access to the natural gas network is also an important factor that affects residential fuel choice, though the issue has received relatively little attention in the literature. Mansur et al. (2008) find that US households with network access make different consumption choices compared to those without access. They are unable to determine if those differences in consumption choices are solely due to network access and consequently analyse fuel choice (and conditional demand) separately for households with and without network access. Couture et al. (2012) take a different approach and include network access as a covariate within a multinomial logit model of fuel choice in the Midi-Pyrénées region of France. Grid 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.

In addition to the literature on fuel choice decisions there is a parallel literature on the acquisition of energy-using assets, e.g. a residential heating system, that is also relevant. One side of that literature has its origin in Bass diffusion models (Bass, 1969) where adoption is modelled as a sigmoidal function over time, with adoption slow at first, then accelerating before reaching a plateau. Applications include modelling households' adoption of heat pumps and photo-voltaic panels as a function of age, education, information, and financial incentives (Hlavinka et al., 2016; Islam, 2014). Energy asset acquisition is also studied in the context of energy consumption with Dubin and McFadden (1984) among the first to highlight that asset ownership is endogenous in an energy demand model. Recent applications include Davis and Kilian (2011) who model natural gas demand in the US and also Mansur et al. (2008), which models fuel choice rather than heating system choice in the context of modelling household fuel consumption. Gertler et al. (2016) have modelled the effect of households' income growth on asset acquisition in the face of credit constraints. Examining refrigerator acquisitions in a developing country,

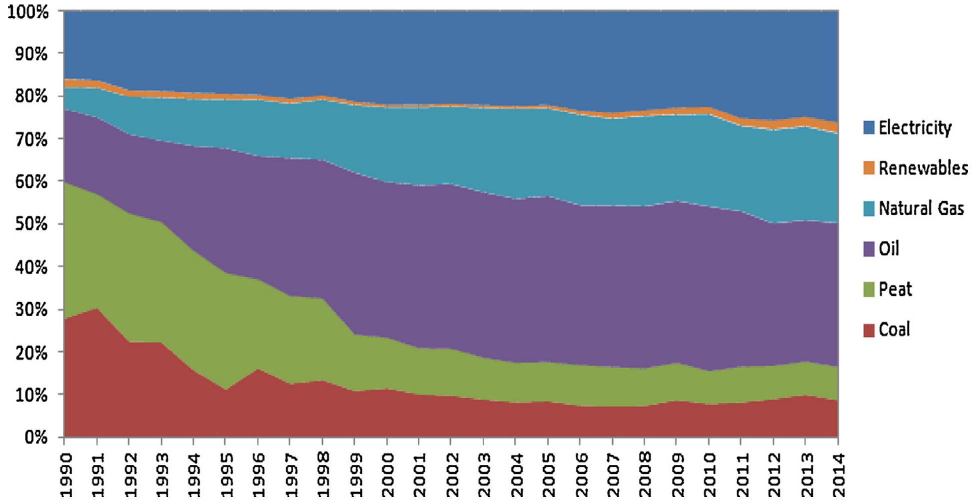

Fig. 1. Residential fuel shares in Mtoe 1990–2014.

Source: Data from http://statistics.seai.ie/

they find that credit constrained households are more likely to purchase energy assets once their income passes a threshold level and furthermore that the threshold level varies depending on the timing of acquisition. This suggests that the impact of network gas availability on heating system or fuel choice is non-linear and cannot be adequately captured with a dummy variable indicating availability of a network connection.

3. Background: residential fuel usage in Ireland

Ireland has a long history of solid fuel usage, and in particular peat usage in the residential sector. Mokyr (2013) cites reports from the 1830's describing the geographical ubiquity of peat and the intensity of its usage. While certain places, such as South Antrim and Limerick had depleted their reserves by this point, it was so plentiful throughout the rest of the country that it was taken for granted, and "people living as little as 4 miles away from a source of turf already considered themselves inconvenienced". Peat continued to be the primary source of fuel for home heating until relatively recently and the geographical relationship between the location of solid fuel resources and its usage persists (Fu et al., 2014). Peat is still commonly harvested from peat bogs by the public and also sold as peat briquettes.

As recently as 1990, the proportion of households using solid fuel as their primary means of space heating was as high as 60%. This had fallen to 16% by 2014.[4] However, 62% of households continue to use a stove, range or open fire as a secondary heating source, and the majority of these use solid fuel.[5]

Comparable residential fuel usage trends in kilo tonnes of oil equivalent from 1990–2014 are demonstrated in Fig. 1. The falling share of solid fuel is evident, which has been replaced by a rise in gas, oil and electricity usage primarily. Renewable energy has not yet established itself directly in domestic heating, however renewable sources accounted for 14.5% of energy inputs to electricity generation by 2014 (SEAI, 2015).

In terms of CO2 emissions, even though final energy use in the domestic sector increased by 26% between 1990 and 2011, energy-related CO2 emissions fell by 2.7%, reflecting the decreasing share of solid fuel usage and the improved efficiency of oil and gas central heating boilers (SEAI, 2013).

3.1. Gas usage

Rogan et al. (2012) provide a comprehensive summary of gas network expansion and usage trends in Ireland between 1990 and 2008. The gas transmission infrastructure had extended to a number of large towns and cities by 1990, however 90% of gas customers were still resident in the two largest cities of Dublin and Cork. That decade saw an expansion of the transmission infrastructure outward from Dublin, along both northeast and southeast coasts and west to the fast-growing commuter towns in the greater Dublin area. The mid-2000s saw an extension westwards linking Dublin with Galway, from here it was further extended to the northwest by the late 2000s. This extension resulted in a constant annual customer growth

4 http://statistics.seai.ie/

5 Solid fuel in this case meaning peat, coal or wooden logs. 67% of those with open fires use solid fuel, and 36% of those with a stove or range continue to use solid fuel. See CSO (2016) for further details.

rate of 9% over the period 1990–2008. There is significant spatial variation however, and by 2014, natural gas customers were still as low as 5% in some western areas (CSO, 2016).

Over this period consumption increased by 470% (Rogan et al., 2012). This was mainly through a growing customer base, changes in the dwelling stock, and changing intensity of usage. Weather effects are also important. From a microeconometric point of view, Conniffe (1996) and Harold et al. (2015) also find weather a strong predictor of seasonal demand. This research also ties in with international research of gas consumption and more general space heating, which find that dwelling characteristics and the socioeconomic characteristics of inhabitants have a significant impact on demand (Rehdanz, 2007; Meier and Rehdanz, 2010; Wyatt, 2013).

The following section outlines our methodology and some empirical considerations one must consider when modelling adoption at area level.

4. Methods

The utility consumers receive from adopting gas central heating is likely to be a function of a range of factors such as the relative price of gas compared with alternatives, along with their socioeconomic and dwelling characteristics. Physical constraints on adoption exist and will relate to each household's proximity to the gas infrastructure. The key price variable at a spatial level is the connection cost. This is a function of distance to the network and is captured by a variable which measures the average distance of all dwellings in each area to the nearest point on the network. Unfortunately relative fuel price data does not exist at a cross-sectional level. However, provided this does not vary across areas for a given period it will be included in our intercept, and as discussed above relative fuel prices may play less of a role than other factors in developed economics.

Economic theory suggests that households will adopt mains gas central heating if the benefits derived from adoption exceed the costs and there is an expected utility increase from doing so. However, innovations take time to diffuse, and households regularly make suboptimal choices. This can be related a range of factors, such as uncertainty about the relative costs or benefits of adoption, indifference, heterogeneity in consumer preferences or lack of access to financing.

In order to estimate the determinants of gas connections at a local area level, it is necessary to consider demand and supply simultaneously. Suppliers are likely to extend the gas network to areas with a higher probability of adoption, and only those households in close proximity to the gas infrastructure can adopt. Previous research has indicated that dwellings with piped gas in Ireland have higher incomes, partly due to their urban location (Watson et al., 2003). This endogeneity could potentially lead to our coefficients being biased if we simply estimate a demand equation. Therefore, we first estimate a supply equation in a two-stage least square regression. The choice of instrument and identification are described in detail in Section 4.3 and instrument validity in Section 4.4.

We assume that the proportion of gas users in any area j will be a function of the aggregate socioeconomic characteristics of that area X_j, aggregate dwelling characteristics D_j, spatial factors which will vary by location S_j and the length of time the gas network has been located in an area $t - t_j^0$. This can be summarised as follows:

$$\frac{\sum_{j=1}^{N_j} G_{ijt}}{N_j} = f(X_j; D_j; S_j; t - t_j^0) \tag{1}$$

where G_{ijt} is a binary variable equal to one if household i in area j uses gas at time t and equal to zero otherwise. N_j is the number of households in each area.

4.1. Supply equation

As adoption might have a non-linear relationship with the length of time the network has been in place, we estimate two supply equations. In the first equation, the dependent variable is the length of time the network has been in place in each area, the second dependent variable is the squared length of time the network has been in place in each area.

Our first-stage supply equations are summarised below:

$$T_j = \alpha + \beta_Z Z_j + \beta_X X_j + \beta_D D_j + \beta_S S_j + \epsilon \tag{2}$$

$$T_j^2 = \lambda + \gamma_Z Z_j + \gamma_X X_j + \gamma_D D_j + \gamma_S S_j + \delta \tag{3}$$

We regress time and time squared on our instrument set Z_j consisting of household count, household count squared, area and area squared.

This generates predicted values for time and time squared which we can use to identify the effect of these factors in our second-stage demand equation. All other variables from the second stage are also included in the first stage regression. We implement a two-stage, generalised method of moments specification (GMM), with common intercepts (α, λ) and errors (ϵ, δ).

4.2. Demand equation

The dependent variable in this regression is the proportion of households in each area that use gas as their primary source of central heating. When completing the 2011 Census, households were asked to select from a range of options the one that best describes their primary means of central heating. This is summarised in Table 1 in Section 5.1.

The demand equation takes the estimated time and time squared from the supply equations, along with a range of socioeconomic and dwelling characteristics, some spatial variables representing the proximity to the gas network, proximity to alternate fuel sources and policy variables prohibiting the sale and burning of bituminous coal.

$$\frac{\sum_{j=1}^{N_j} G_{ijt}}{N_j} = \nu + \delta_{\hat{T}}\hat{T}_j + \delta_{\hat{T}^2}\hat{T}_j^2 + \delta_X X_j + +\delta_D D_j + \delta_S S_j + \mu \tag{4}$$

We include a range of socioeconomic factors at area level, which might influence the decision to adopt gas central heating. These are related to economic status, age, education levels and tenure type. Dwelling characteristics include house type, a measure of energy efficiency (Building Energy Rating – BER), and dwelling age. All of these variables are expressed as proportions for each Small-Area.

4.3. Identification

As described above, we use household count, area size and their squared terms in our first-stage supply regression to generate predicted values for time and time squared in the second stage demand regression. This is because the network operator is likely to expand the network first to those areas with a higher probability of adoption. This might bias our results unless accounted for.

The rationale behind this instrument is that the total costs of extending the network to an area should be inversely related to the number of customers in an area. If diminishing economies of scale exist, a negative relationship will also exist with the square of the number of customers. In addition to this, the density of households will also be an important factor in driving network extensions.[6] This instrument captures the key element being the utilities' decision to extend the network to certain areas based on local economies of scale. This empirical strategy draws from Lyons (2014) in his estimation of the timing and determinants of local broadband adoption in Ireland.

As the network has been developed over a long period of time (approx. 100 years) using population data from 2011 is not a perfect measure. However we do not have historical series for population at Small-Area level, and the geographic spread of population in the current period is likely to be highly correlated with past periods.

On the demand side, the key factor driving adoption will be the cost and availability of the network connection, this is captured by our supply-side instruments and the variable measuring distance to the network. One could argue that uptake may also be affected by neighbourhood spillovers, for example if a household observes a number of neighbours connecting to the network and then decides to connect. Further, imperfect information, neighbourhood effects or other factors may affect the timing of adoption. This underlines the importance of examining the time lag in adoption. While we can measure the magnitude of the time-lag and how is varies by area, our data do not allow us to unpick the underlying reasons behind it.

4.4. Instrument validity

Regarding instrument relevance, Baum et al. (2007) suggest using Kleibergen–Paap rk statistic to test for underidentification when using a robust covariance estimator, and the corresponding Wald F statistic when testing for weak identification. In both cases the results of these tests fail to reject the null hypothesis that our instruments are underidentified and weakly identified, as per Table B1. This is likely to be the case because we are including interactions of endogenous variables (linear and quadratic terms) in our estimations and these are highly correlated. Wooldridge (2010) suggests that when this is the case, one should check whether the most general linear version of the model is identified and if this is not the case, proceed with caution. In our case both the linear and quadratic endogenous variables are strongly identified when estimated separately, Table B1, and we proceed on that basis.

The result from the Hansen *J* test of overidentifying restrictions suggests that we do not reject the null hypothesis that the overidentifying restrictions are valid for the 100 year sample. At a 5% level we would reject the null for the 20 year sample. However, some doubt has been cast on the ability of this test to provide information on the validity of the moment conditions implied by the underlying economic model (Deaton, 2010; Parente and Silva, 2012). Parente and Silva (2012) in particular suggest that this should more accurately be considered a test of instrument coherence, as opposed to validity.

[6] By including count and area we implicitly account for density while also accounting for scale. Robustness tests are also conducted using household density and the results hold.

5. Data

The data in this paper come from a range of sources. The proportion of natural gas users within each area, along with area proportions of socio-demographic and dwelling characteristics were obtained from the Central Statistics Office (CSO) Census of Population, Small-Area Population Statistics 2011. Gas Networks Ireland (GNI) provided detailed GIS maps, including the timing and geographic location of the high-pressure (HP), medium pressure (MP) and low pressure (LP) gas network. The Environmental Protection Agency's (EPA) website provide GIS maps of soil types in Ireland, from this we calculated the average distance to bogs for all dwellings in each location. The EPA also provide information on the timing and location of smoky-coal bans in Irish urban areas[7]. For descriptive statistics of all variables used in estimations, please see Appendix A.1.

The analysis is conducted at Small-Area level. This is the most disaggregated unit for which one can obtain publicly available Census data in Ireland. These range in population from 8 to 549 dwellings. There are over 18,000 Small-Areas in Ireland. Our sample consists of 9638 Small-Areas which are all in close proximity to the gas network.

5.1. Dependent variable

The dependent variable is the proportion of gas users within each Small-Area. This was self-reported by households as per Table 1. Natural gas usage accounted for almost a third of all primary central heating in the national population in 2011. We explore how this varies by recalculating the proportions of each fuel used as the average distance of all dwellings in a Small-Area get closer to the gas network. The average proportion of gas users jumps to 57.5% in areas within 1000 m of the network (our sample), and increases as the average distance to the network falls. The main fuel displaced is oil, and electricity is increasing used as an alternative. This reflects the greater proportion of electric heating in urban apartment buildings close to the gas network.

However, even within these areas, considerable variation exists in the proportion of users. Fig. 2 illustrates that even for areas in which the average distance of all households to the nearest point on the low or medium pressure network is less than 100 m, a significant proportion do not use gas as their primary means of heating.

This is illustrated geographically in Fig. 3. As examples we choose four metropolitan areas in Ireland, all of which have access to the gas network. Outside of Dublin, Cork has both the greatest number and highest proportion of households using natural gas as their primary means of central heating, however there is still significant local variation. Galway has a relatively low proportion of gas users in most areas, reflecting the recent extension of the network to this city.

5.2. Gas network

The location of the gas infrastructure in Ireland is displayed in Fig. 4. As described in Section 3.1, the network location was concentrated mainly in larger cities such as Dublin and Cork until relatively recently. The high-pressure network was expanded to link Limerick and Galway in the early 2000s.

Detailed network maps, which also contain the date each individual segment was laid, were obtained for each segment of the gas network. From this we calculate when the gas network was put in place for each Small-Area.

5.2.1. Mean distance to LP or MP network

This distance variable was generated by calculating the distance of every domestic residence in the CSO 2011 Census to the nearest point on the LP or MP gas network (Krah et al., 2016). We then aggregated by Small-Area, to calculate the average

Table 1
Census 2011 primary central heating proportions.

What is the main type of fuel used by the central heating in your accommodation?	National population	Within 1000 m	Within 500 m	Within 100 m	Within 50 m	Within 10 m
No central heating	1.6%	1.3%	1.3%	1.3%	1.3%	2.8%
Oil	43.1%	23.9%	22.3%	18.2%	16.2%	3.2%
Natural gas	33.4%	57.5%	59.2%	64.0%	67.1%	69.7%
Electricity	8.5%	11.5%	11.7%	11.8%	11.1%	19.5%
Coal (including anthracite)	4.8%	2.5%	2.4%	2.0%	1.8%	1.5%
Peat (including turf)	4.8%	0.8%	0.7%	0.4%	0.2%	0.1%
Liquid Petroleum Gas (LPG)	0.6%	0.3%	0.3%	0.2%	0.2%	0.2%
Wood (including wood pellets)	1.3%	0.3%	0.3%	0.2%	0.2%	0.1%
Other	0.5%	0.3%	0.3%	0.2%	0.2%	0.3%
Not stated	1.4%	1.6%	1.6%	1.7%	1.7%	2.7%

Notes: Author's calculations based on CSO Census 2011 data.
Data presented for national population and for varying distances from gas network.

[7] This can be accessed at http://gis.epa.ie/

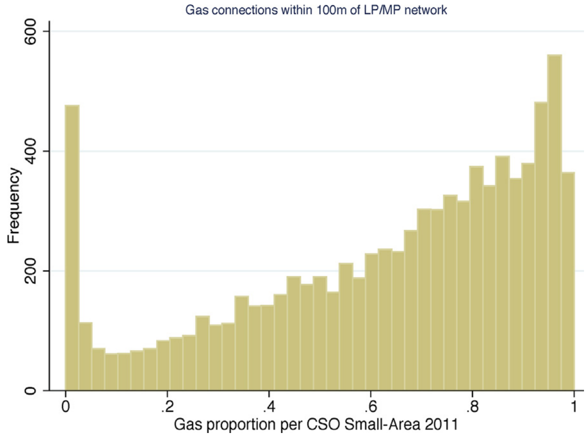

Fig. 2. Proportion of households using gas as their primary fuel in close proximity to the low pressure gas network.
Source: Author's calculation using Census 2011 data.

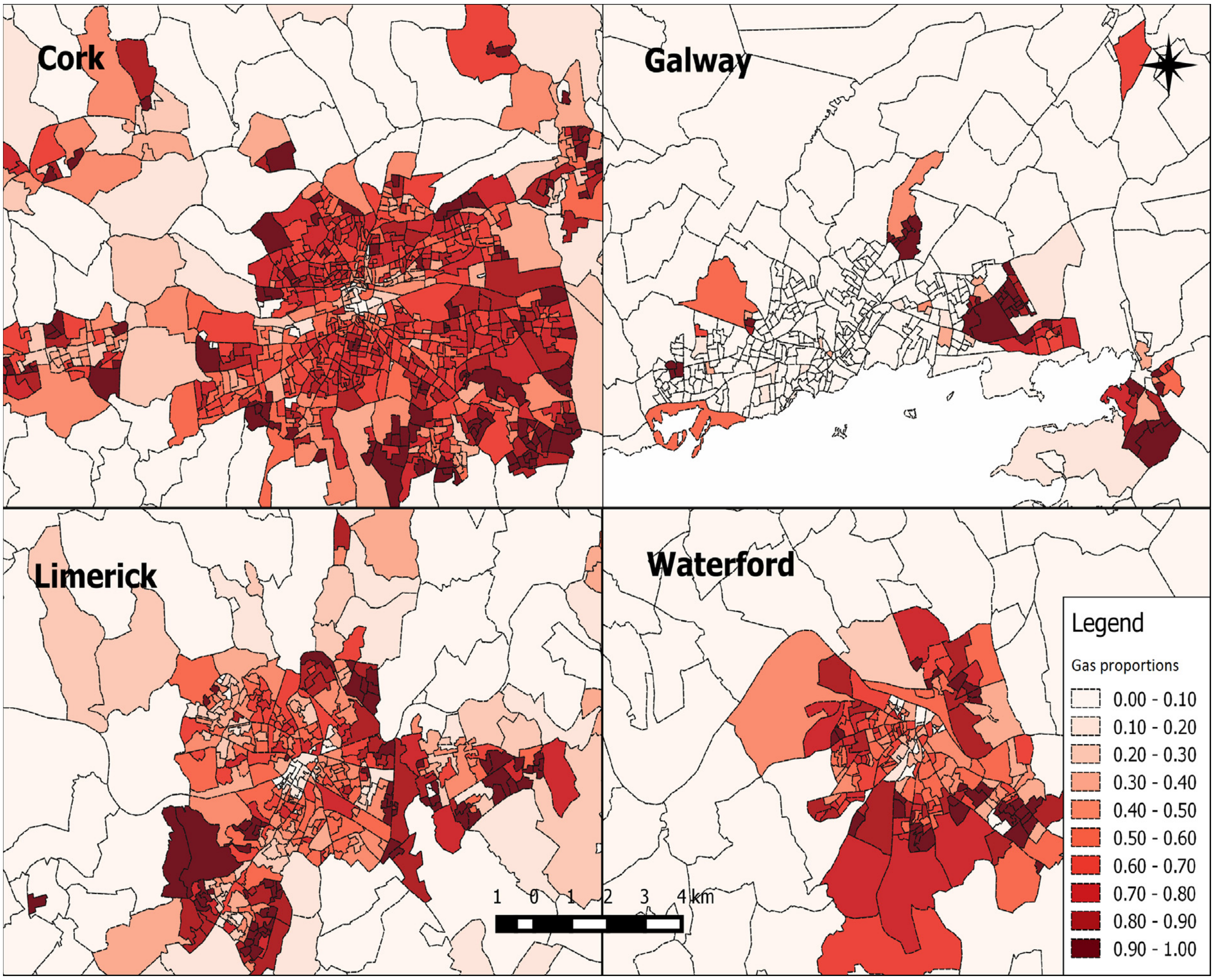

Fig. 3. Spatial variation in gas connections at Small-Area level in four Irish metropolitan areas.
Source: Author's calculation using Census 2011 data.

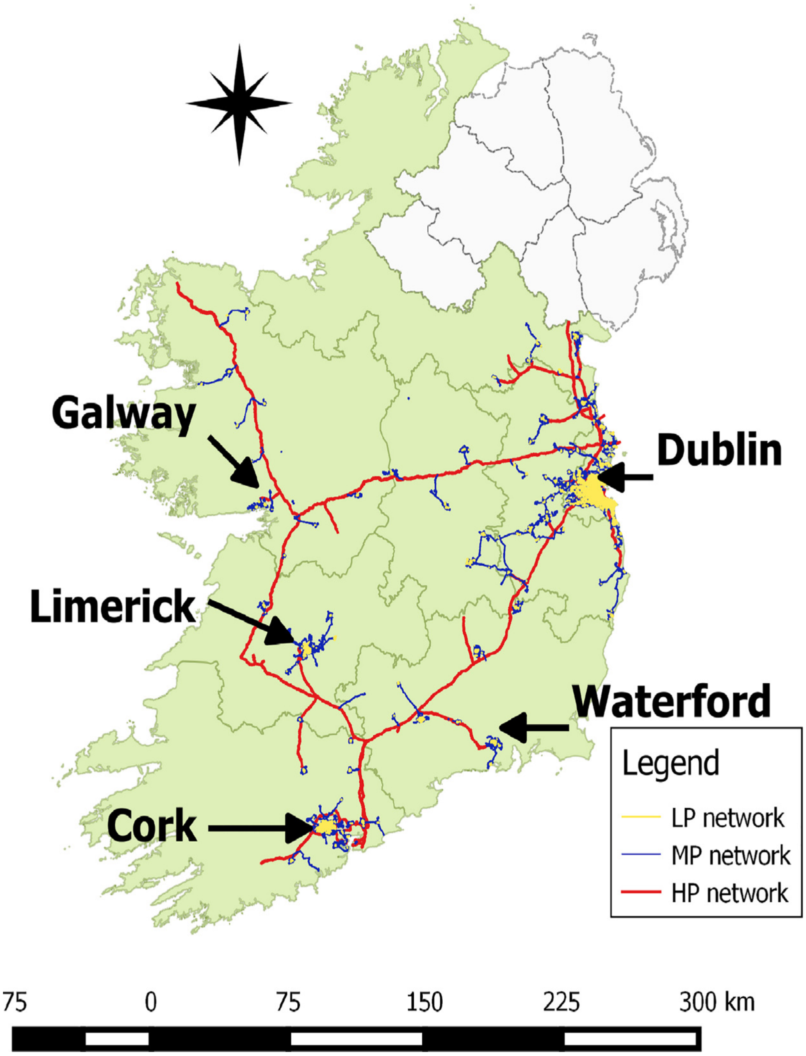

Fig. 4. Location of Irish gas network infrastructure 2011.
Source: Data provided by Gas Networks Ireland – please see the disclaimer at the end of this document.

distance for each area. This variable will reflect the relative ease of connection for various areas. This can vary even within close proximity to the network – as can be seen from Fig. 5.

5.2.2. *Date network was laid*

Each segment of the gas network[8] has a date identifier marking the day that portion of the network was laid. Using GIS software, we map each network segment to any Small-Area it is fully within or intersects at any point, illustrated in Fig. 6. This generates a distribution of date variables for each Small-Area. As the 2011 Census (from which we take our gas proportions data) took place on April 10th 2011, we consider this as time t. From this we calculate the length of time in years since each segment was laid as $t - t_j^0$, where t_j^0 is the date each segment was laid. This generates a distribution of year-length variables for each Small-Area. As a proxy for the length of time gas was available to households in each area we choose maximum time length, i.e. the date the first segment was laid in each area. However we also run estimations with various other time variables, such as the average time and latest time gas became available in each area.[9]

[8] The low pressure network contains 135,195 separate segments, the medium pressure network contains 123,048 segments.

[9] We are missing a date identifier on approximately 20% of the MP and LP networks. This may introduce some error into the estimation but we have reduced it substantially through aggregation. When we aggregate to area level, there remains only 3% of Small-Areas for which we have no date identifier. Robustness checks are also performed which test the sensitivity of results to missing date identifiers.

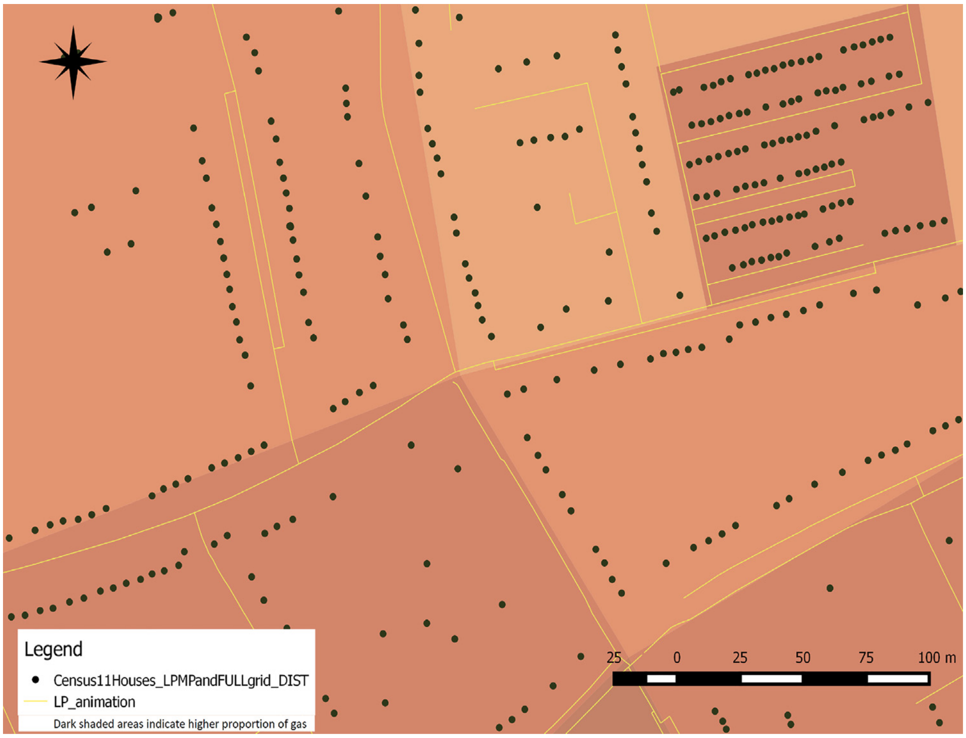

Fig. 5. Variation in household density and location in close proximity to the low pressure gas network.
Source: Data provided by CSO Population Census; Gas Networks Ireland – please see the disclaimer at the end of this document.

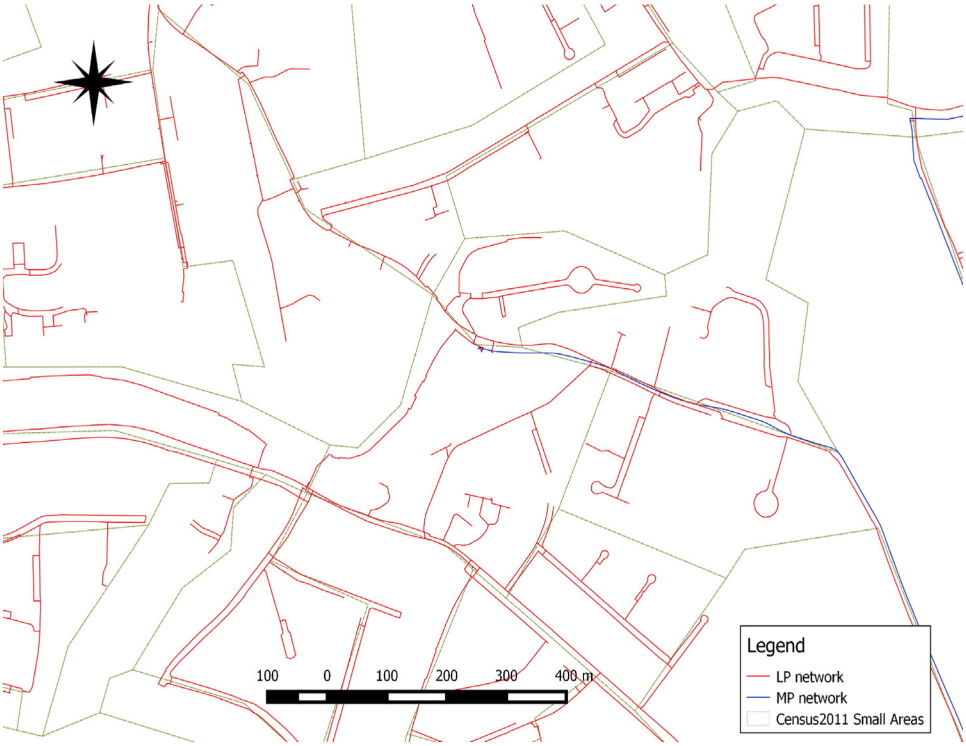

Fig. 6. Example of Small-Area boundaries and gas network.
Source: Data provided by CSO Population Census; Gas Networks Ireland – please see the disclaimer at the end of this document.

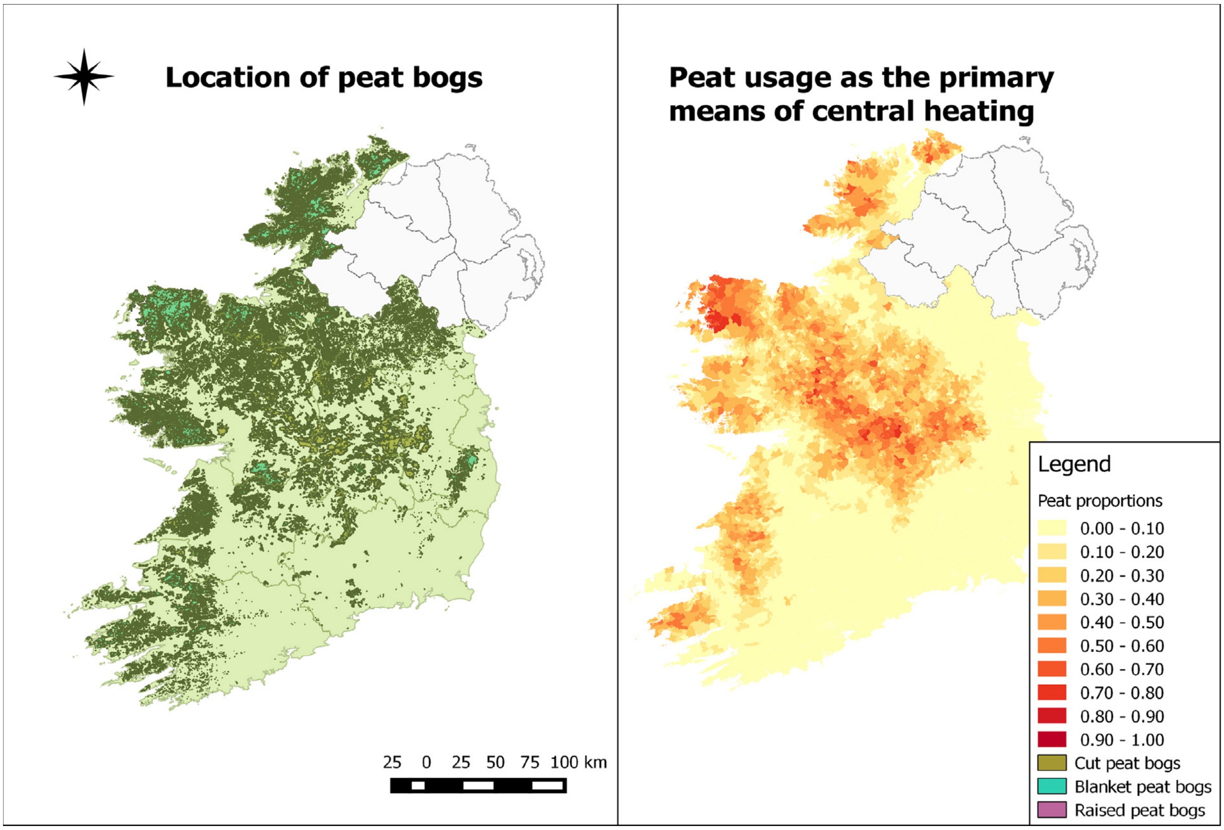

Fig. 7. Location of peat bogs and areas where peat burning is the primary means of central heating.
Source: Data provided by CSO Population Census; EPA GIS portal.

5.3. *Spatial fuel source and policy variables*

From Census 2011 4.8% of households in Ireland use peat as their primary heating source, however a sizeable proportion also have an open fire or peat burning stove as a secondary source. As can be seen from Fig. 7, this pattern is highly correlated with the location of peat bogs. Using GIS software we calculate the distance of every household to the nearest raised and blanket bog. Again, we aggregate these variables to Small-Area level, allowing us to determine the relative proximity of dwellings in each area to different bog types.

A ban on the marketing, sale and distribution of bituminous fuel (or "smoky coal ban") was introduced in Dublin in 1990.[10] This was in response to severe instances of winter smog. This ban was extended to an increasing number of towns with a population in excess of 15,000 people between 1990 and 2013, and a prohibition on burning was introduced in addition to the ban on marketing, sale and distribution. By 2011 this was in place in 19 towns in Ireland. Information on the location of these bans allow us to overlay this onto our Small-Areas. Dummy variables are then created for these areas. While we cannot infer a causal relationship between this policy and gas usage, we can examine the correlation, holding other factors constant.

5.4. *Census and other data*

Supplementing the spatial and temporal data on fuel sources and policy variables, we include a range of socioeconomic, demographic and dwelling variables from the Census in our estimations. These variables are all at Small-Area level and thus will reflect the aggregate characteristics of each area. We also include information on the energy efficiency of dwellings. This data was estimated using the SEAI BER database and the Census of population 2011. For more information see Curtis et al. (2015). We use the proportion of low-rated (E,F,G) dwellings in each area.

[10] See http://www.environ.ie/environment/air-quality/coal/smoky-coal-ban

6. Results

We estimate a generalised method of moments (GMM) instrumental variables specification, with household count, area and their squared terms as instruments. The length of time the network has been in place might affect the proportion of users in a non-linear manner. For example, to run mains gas to certain housing estates adjacent to the existing network GNI require a minimum proportion of households within that area to adopt immediately.[11] This would result in a large initial uptake which mitigates over time. Alternatively for one-off connections, certain households might be slow to switch to mains gas when it first becomes available, due to sunk costs related to their current heating system. This might result in a slow initial uptake, followed by more rapid switching. To accommodate this, we specify two first stage regressions, with time and time squared as the dependent variables. Standard errors are robust to heteroskedasticity. Areas are weighted by population in all specifications. We restrict our analysis to areas in which the average distance of all dwellings is less than 1km from the nearest point on the low or medium pressure gas network. Other areas are not relevant for our analysis, as it would not be feasible for households within them to connect to mains gas.[12] We report the results from our first stage supply equations first, followed by the second stage demand equation.

6.1. Supply equations

These equations are primarily used to identify the length of time the network has been in place in our demand equation. The instruments are all significant and have the expected signs. The gas network was located first in areas of high density. We include all other covariates from our second stage in the first stage regressions, as there is no efficiency loss from doing this. However, as many of them, particularly those related to socioeconomic characteristics, reflect current factors and the gas network was constructed over many years, their interpretation is subject to caution. The results are reported in Section A.1 of the appendix.

One variable of interest though is the proportion of houses built in various time periods in each area. This will reflect changes in the housing stock over time. As one might expect the coefficients on these terms are highest for those areas with high proportions of pre 1945 dwellings, decreases for areas with higher proportions of building constructed between 1945–1980, and rises again for buildings constructed between 1980–2000. This effect is indicative of the outward sprawl of network infrastructure from areas of historically high density over time.

6.2. Demand equation

Predicted values for length of time and length of time squared are generated from the first stage estimation. The proportion of gas connections in each area is then regressed on these and other variables. We report results for both the whole 100 year sample and the more recent 20 year sample in Table 2. The results indicate that each additional year the network has been in place results in a 3.2 percentage point increase in the proportion of households within that area who use gas as their primary fuel. This effect mitigates over time, as indicated by the negative effect on the squared term. We can graphically illustrate the time-path to adoption including both linear and squared terms, as per the left-hand panel of Fig. 8. Both of these effects are highly statistically significant. On average, for all areas in our estimation there is an increasing adoption up to about 25 years in the full sample. The limiting factor is due to certain areas having had access to the gas network for up to a century, but which still do not have a very high proportion of connections. When the analysis is restricted to more recent periods the rate of adoption appears to be much faster. This is graphed in the right-hand panel of Fig. 8. When the sample is restricted to the previous 20 years, each additional year is associated with approximately a 12 percentage point increase in gas customers, again this effect appears to reduce over time. This is broadly in line with Rogan et al. (2012), who reported an annual increase of 9% between 1980 and 2010. On average, penetration rates are reaching about 50% after 8–10 years.

The results for both 100 year and 20 year sample are broadly similar for most of the remaining variables. We will discuss both together, unless otherwise stated, with the 20 year results in parenthesis. The coefficient on the variable representing distance to the gas network is significant at the 1 percent level. Even in areas that are relatively close to the network, distance still matters. Interpreting this result implies that a 1 percent increase in average distance to the network is associated with a 12 (13) percentage point reduction in the proportion of users in an area. This reflects the cost of domestic connections. For houses within 15m of the network connection costs are € 220, with a charge of € 45 for each additional metre beyond this.[13]

The distance to a cut bogs (this includes both raised and blanket bogs) has a positive coefficient, indicating that the further away an area is from a cut bog, all else being equal, the higher the proportion of gas users in that area. The coefficient on

[11] See for details http://www.cer.ie/document-detail/Gas-Networks-Ireland-Connections-Policy-Review/1007

[12] We test the sensitivity of this parameter to various distances from 100 m upwards.

[13] https://www.gasnetworks.ie/home/get-connected/connection-costs/

Table 2
Second stage demand equation.

Dep Var: proportion of gas users by SA in 2011					
Variable category	Variable	100 year sample		20 year sample	
		Coefficient	Robust SE	Coefficient	Robust SE
Spatial fuel and policy variables	Maxlengthyears hat	0.032***	(0.004)	0.119***	(0.022)
	Maxlengthyears squared hat	−0.001***	(0.000)	−0.006***	(0.002)
	log(distance to cut bog)	0.019***	(0.004)	0.038***	(0.006)
	log(distance to bkt bog)	−0.006	(0.005)	−0.020***	(0.005)
	log(mean distance to gas network)	−0.120***	(0.006)	−0.129***	(0.007)
	Coalban dummy	0.063***	(0.011)	0.106***	(0.016)
Socioeconomic	**EconWorking**	**[REF]**		**[REF]**	
	EconLooking for first job	−0.289	(0.313)	0.076	(0.243)
	EconUnemployed	−0.427***	(0.123)	−0.659***	(0.128)
	EconStudent	−0.398***	(0.130)	−0.240**	(0.103)
	EconHome	−0.303*	(0.155)	−0.438***	(0.127)
	EconRetired	−0.774***	(0.198)	−0.564***	(0.144)
	EconDisabled	−0.710***	(0.175)	−0.438***	(0.121)
	EconOther	−0.150	(0.198)	−0.415	(0.275)
	Age 25–44	**[REF]**		**[REF]**	
	Age 0–14	0.560***	(0.117)	0.405***	(0.084)
	Age 15–24	0.188	(0.156)	0.106	(0.118)
	Age 45–64	−0.293***	(0.099)	−0.039	(0.109)
	Age 65 plus	1.046***	(0.239)	0.458***	(0.165)
	EduSecondary	**[REF]**		**[REF]**	
	EduPrimary	0.187**	(0.082)	0.400***	(0.076)
	EduTechnical	−0.124	(0.100)	−0.225***	(0.086)
	EduDegreeplus	0.253***	(0.059)	0.198***	(0.042)
	EduRefused	−0.029	(0.128)	−0.041	(0.086)
Socioeconomic	**TenOwnmortgage**	**[REF]**		**[REF]**	
	TenOwnNomortgage	−0.351***	(0.064)	−0.536***	(0.069)
	TenRentland	−0.153***	(0.044)	0.001	(0.046)
	TenRentlocal	0.119**	(0.049)	0.073**	(0.031)
	TenRenvol	−0.009	(0.081)	0.078	(0.078)
	TenRentfree	−0.252	(0.203)	0.177	(0.271)
Dwelling	**DwellBungalow**	**[REF]**		**[REF]**	
	DwellFlat	−0.219***	(0.026)	−0.166***	(0.020)
	DwellBedsit	−0.192	(0.358)	−0.847***	(0.120)
	DwellOther	−0.317**	(0.133)	0.285	(0.181)
	Proportion EFG	−0.499***	(0.036)	−0.602***	(0.034)
	Age Post 2006	**[REF]**		**[REF]**	
	Age Pre 1945	0.446***	(0.075)	0.713***	(0.108)
	Age 1945–60	0.363***	(0.056)	0.577***	(0.072)
	Age 1960–80	−0.126***	(0.033)	0.235**	(0.101)
	Age 1980–2000	−0.126***	(0.025)	0.156*	(0.082)
	Constant	0.840***	(0.097)	0.592***	(0.108)
Diagnostics	*N*	9638		7965	
	F(34, 9603), (34, 7930)	461.38	(0.00)	416.62	(0.00)
	Overid – Hansen *J*	1.341	(0.512)	6.836	0.0328

Notes: Results from IV-GMM specification. Cluster-robust standard errors in parenthesis.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

uncut blanket bogs is negative, but not significant.[14] This is likely to be the case because the current proportion of households using solid fuel in an area will reflect past incentives in that area. Therefore proximity to cut bogs might be a better indicator of fuel usage as this will reflect areas where peat has been harvested over many years. The ban on the sale and burning of bituminous fuel appears to also have had an effect. All else being equal, these areas have a 6 (11) percentage point higher proportion of gas users. We cannot infer causality however.

Considering the socioeconomic and dwelling variables next, our reading of the coefficients changes. For each set of variables, we interpret the effect relative to the reference category. All of these variables are area proportions. The employment status variable indicates that, all else equal, compared to areas with higher proportions of people in employment, all other

[14] A number of blanket bogs are located in the Wicklow mountains, in close proximity to Dublin, which has the largest concentration of gas users. This is likely to be driving the negative coefficient of this variable.

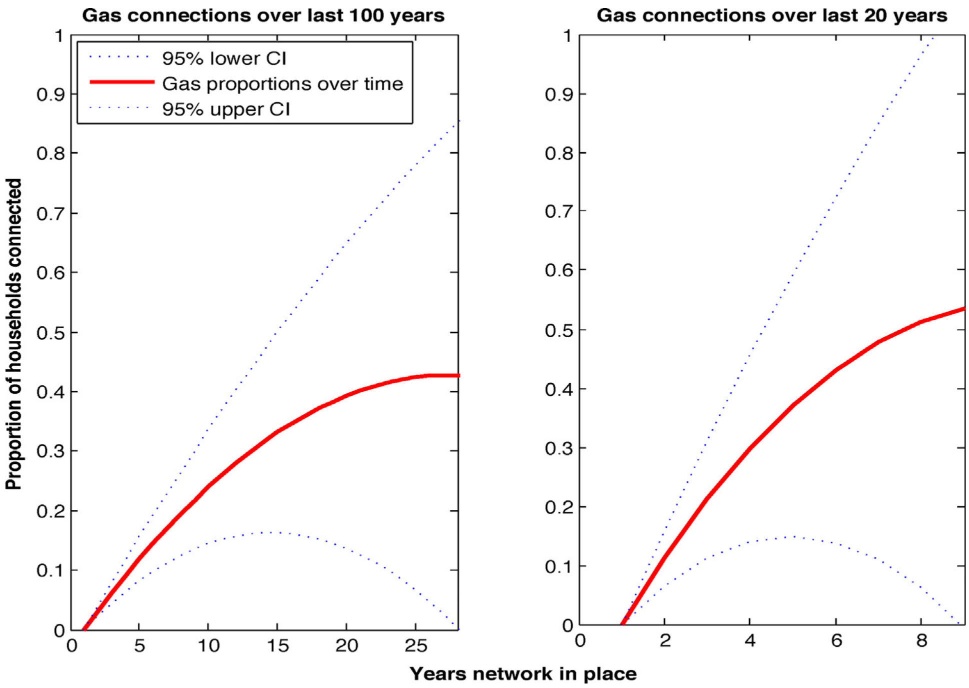

Fig. 8. Proportion of gas adopters at Small-Area level over time.

categories have reduced gas connections, although not all coefficients are statistically significant. Taking the "EconUnemployed" variable as an example, our interpretation is that all else equal, a 10 percent increase in the proportion unemployed, relative to the reference category (those in employment), is associated with a 4.27 (6.59) percentage point decrease in the proportion using natural gas.

Areas with high proportions of young families and elderly people are also associated with greater gas connections, compared to those with high proportions of 25–44 year olds. Considering tenure type next, those areas with higher proportions of outright homeowners and private renters are less likely to have gas connections than those with high proportions of mortgage holders. However, local authority areas have higher proportions of gas connections.

Areas with high proportions of houses, as opposed to flats or bedsits (studio apartments) are more likely to use gas. This reflects the large proportion of electrical heating in apartment complexes in Ireland. The proportion of low-rated BER dwellings in an area is strongly negatively associated with gas connections.[15] Finally, when looking at the 100 year sample we can see that both very new (post 2000) and very old (pre 1960) constructed houses are more likely to have high proportions of gas connections. This likely reflects the urban location of a high proportion of the older building stock. The coefficients differ slightly for the 20 year sample, with more recent network expansions extending to a higher proportion of dwellings built from 1960–1980.

There is a high degree of collinearity between some of the socioeconomic and demographic variables. For example, areas with high proportions of retired people also have high proportions of people aged over 65, and have a high proportion of owner occupiers without any remaining mortgage obligations. While each of these variables is compared with the reference category in each class, caution is advisable in interpreting some of these coefficients. For example, the results indicate that areas with greater proportions of retired households are less likely to have high connections to the gas network than areas with greater proportions employed. However, areas with greater proportions aged over 65 are more likely to have high gas connections than areas with greater proportions of 25–44 year olds. This result seems contradictory, but is driven by the reference category changing in each case, and a small number of areas, with very high gas connections, which also have households aged over 65 on average, that are not in retirement.

7. Scenario analysis – gas network expansion

The model may be used as a tool to predict residential uptake of future gas network expansion as well as assess the associated impact on greenhouse gas emissions. Network expansion is still ongoing with a number of provincial towns earmarked for connection. Wexford town, which is located in the south-east of the country, is one town where the network

[15] While not reported in the tables, additional analyses were conducted using the proportion of AB and CD rated properties. Higher proportions of AB properties are strongly associated with more gas connections, while the effect of high proportions of CD properties is weakly positive.

Table 3
Projected proportions of gas network connections.

After:	Small Areas	% Households connected	Minimum %	Maximum %	change emissions tCO_2/year
2 years	74	0.19	0.01	0.21	−23,065
4 years	74	0.36	0.17	0.38	−44,617
6 years	74	0.48	0.29	0.50	−61,651
8 years	74	0.55	0.36	0.57	−67,614
10 years	74	0.57	0.38	0.59	−70,815

has recently expanded and is a useful case study for model simulations. The town comprises 74 Small Areas, which are the observation unit in the estimated model. Based on the 2011 population census there are 17,684 people living in these Small Areas within a housing stock of 8437 residential units. These areas include a spectrum of building types, as well as socio-demographic characteristics of the occupants. Houses are the most frequent residential unit, with a mean across the 74 small areas of 87%, though this varies from a minimum of 19% to a maximum of 100% across Small Areas. The mean share of older pre-1945 properties is 17% ranging from a minimum of 0% to a maximum of 79%, which reflects both the older central parts of town and more recently build areas on the periphery. While the property type, and age may present different engineering challenges connecting to the gas network an important additional consideration is the property's occupants. The model incorporated four socio-demographic variables covering the head of household's socio-economic status, age and education, as well as details on property tenure. The proportion of households with a working head of household varies between 22% and 70% across Small Areas; those with a university degree range from 6–42% with similarly broad variations in age. Approximately 25–32% of properties are either owner-occupied (with/without a mortgage) or rented from a private landlord while 10% are rented from a public landlord. The maximum proportion of each of those tenure categories is between 63–73%, while the minimum varies between 0–6%. The adoption of gas as a fuel is likely to differ substantially given the wide variation both in building characteristics and their occupants. The estimated model is an ideal tool to predict gas connections by Small Area with the passage of time, which should aid in planning network expansion.

To complete the simulation we make a number of assumptions. First, we use the model estimates based on gas network connections in the past 20 years, as this is likely to have more relevance for predicting network connections over a short-term horizon. To calculate the impact on emissions, data on the fuel used prior to gas connection (i.e. coal, oil, etc.) as well as the quantity consumed is required. Mean household fuel consumption by heating source type are based on figures reported in Leahy and Lyons (2010). The pre-switching fuel type assumption is based on an analysis of the composition of fuels consumed in Small Areas with network gas connections at 5% increments in share of gas network connections.

The projected network connections are reported in Table 3. With the model's estimated inflection point occurring at approximately 10 years, implying that the level of connections reaches a plateau after that time, we do not report predictions beyond 10 years. Within 2 years the mean share of connections is 19%, which is relatively high but as the Small Areas differ in size the mean share is not equal to the proportion of all households connected. The level of connections differs considerably with the connection share being as low as 1% or as high as 21% in some Small Areas. The level of connections increases quite rapidly over the first 8 years reaching a plateau just below 60% mean share of gas connections by Small Area, though the share of connections is substantially lower in some places with 12% of Small Areas not exceeding a 50% connection rate. The switch to gas is primarily from oil (mostly kerosene) and also solid fuels such as coal. The projected reduction in emissions associated with fuel switching is also reported in Table 3. Emissions reductions reaches 70 $ktCO_2$ per annum after ten years, which is approximately 1% of emissions from the entire Irish residential sector in 2015.[16] Based on these projections the further gasification of residential heating represents a major opportunity to substantially reduce greenhouse gas emissions in the coming years.

8. Robustness and sensitivity analysis

This section explores a range of alternative model specifications. For reasons of brevity the focus is on our baseline 100 year sample, but results hold for both unless otherwise stated. Reported second stage demand equation results are reported in the Appendix.

8.1. Alternative model specifications

The first set of additional estimations examine alternative model specifications. Column 1 in Table C1 presents results where household density and household density squared are used instead of household count and household count squared for the instruments. The results remain quite stable compared to our main estimation. This is likely because by instrumenting with household count, area and their square terms in the main estimation we implicity account for density.

[16] http://www.epa.ie/climate/emissionsinventoriesandprojections/nationalemissionsinventories/

Another source of concern with our main estimations is that we do not explicitly account for household income. Information on incomes is not available at Small-Area level and although we capture a wide range of socioeconomic factors correlated with income some bias may exist due to its omission. To account for this we estimate two additional models which include proxies for income. Column 2 presents results using the Trutz Haase HP Deprivation Index (Haase and Pratschke, 2012) for each Small-Area. This is a composite measure created by combining a range of Census variables, some of which we had included in our main specification. To avoid potential multicollinearity we omit these variables from this set of results (employment status, age, education and tenure type). Column 3 includes a variable which captures average relative employment compensation for each county from 1995–2011. Standard errors are clustered at county level for these estimations. In both cases these variables are significant and have the expected sign. Coefficients on the predicted length of time variables remain stable in both estimations. The statistical significance reduces for some of the distance variables in Column 3 – otherwise results remain quite stable. While the Trutz Haasee is a useful measure in its own right, it is essentially an aggregation of variables already included in our model and does not provide much additional information. Including county level relative income is a useful measure, and given that counties are administrative boundaries (as opposed to Small-Areas) clustering the standard errors at this level would make sense to control for any factors that affect groups of observations uniformly within each county. However, we are less confident about the accuracy of this specification as when clustering at county level the number of clusters are insufficient to calculate a robust covariance matrix.

To account for this in Column 4 we provide a further robustness check in which we cluster standard errors at Electoral Division (ED) level.[17] This allows for a calculation of a robust covariance matrix. However EDs are an arbitrary aggregation of Small-Areas used for Census purposes and it is not clear why intra-group correlation would exist at this level. Given the main results are quite stable across all additional models estimated our main reported models remain our preferred specification.

8.2. Sensitivity analysis on missing gas segment date identifiers

As previously described a date identifier is missing for 20% of the LP and MP network segments. While we mitigate this problem through aggregation at the Small-Area level, measurement error may still bias our results. To account for this we conduct sensitivity analysis on various sub-sets of the data. Columns 1–4 of Table C2 present results where we set an acceptable threshold of missing date identifiers for each Small-Area at 0%, 5%, 10% and 20%. Taking Column 1 for example we omit any Small Area with a missing date identifier. This is quite restrictive and reduces our sample to 5072 Small-Areas. As we move across the columns the sample size increases and results converge towards our main estimates. However, in all cases they are quite stable. Our main model remains the preferred specification as it provides a conservative estimate of the effect of time on gas heating adoption.

8.3. Sensitivity analysis on average distance from gas network

For the main estimations we examine uptake of gas central heating in Small-Areas in which the average distance of all dwellings is within 1000m of the gas network infrastructure. This threshold is chosen as it would be prohibitively expensive to connect over distances much longer than this. Another issue is that a small proportion of dwellings use LPG and while this is considered separately by the CSO and should not be included in our dependent variable, some households may have answered this question incorrectly – particularly if they state they are using natural gas but are far from the network. Results of a range of sensitivity checks are reported in Table C3. As one might expect, results are quite unstable at distances far from the network. Households in these locations would have no realistic chance of connecting. As the threshold moves closer to the network results converge towards the main estimations. Again, our main model remains the preferred specification and it provides a conservative estimate of the effect of time on gas heating adoption.

9. Conclusion

We have examined the determinants of gas central heating adoption at Small-Area level in Ireland, simultaneously modelling supply and demand in order to account for potential endogeneity in network infrastructure roll-out and adoption. We explicitly model the time-path in diffusion, which is important in order to better understand the potential for both policy and technological improvements to aid carbon abatement. Ireland is interesting from an international perspective as it has a legacy and culture of peat usage for home heating. The gas network has been in place in the two largest cities for a century, but only recently extended to other parts of the country. Our unique time and location coded data allow us to examine adoption over an extended period.

On average the results show that over the past century, each year the network has been in place is associated with a 3% rise in connections. When more recent periods are examined, the connection rate is much higher, about 12% rise per year over the past twenty years. There appears to be a non-linearity in these estimates and this effect diminishes over time. Proximity to the network is also an important determinant of connections, and reflects the cost of connection for all dwellings in that area.

[17] There are approx 3400 EDs in Ireland.

The widespread availability of peat as a source of fuel has clearly inhibited the transition to cleaner fuels. As peat usage is highly correlated geographically with the location of peat bogs, it is useful to see how gas network roll-out interacts with the proximity of other fuel sources in determining gas central heating adoption. Proximity to previously cut peat bogs is negatively associated with gas connections. Recent policy developments such as the ban on the sale and consumption of bituminous coal is associated with a 6 percentage point higher proportion of gas connections in these areas, all else being equal. We can't attribute causality here however, as this ban was first introduced in urban areas, which would already have had higher proportions of gas connections before the bans were introduced.

In the context of future network gas expansion the analysis provides a number of useful lessons. As noted above, domestic gas network connections are neither uniform nor instantaneous following network expansion. However, connections do occur relatively rapidly reaching a plateau within 10 years. There is also considerable heterogeneity by socio-demographic characteristics and building attributes across Small Areas in terms of network connections. This information is useful for network planners in deciding where to next extend the network, and also for commercial suppliers of gas in determining why certain areas in close proximity to the network have low levels of connections. Areas that are more socially deprived, with fewer 'working' households or lower levels of education, having lower rates of network gas connection. Network expansion in such areas may be unprofitable or have longer pay-back periods. If gas network expansion is considered socially desirable in such areas public subvention may be necessary.

One reason why gas network expansion could be considered a public policy objective is because it can contribute to the de-carbonisation of the residential sector. The case study simulation demonstrates the short term benefits of network expansion for greenhouse gas emission reductions associated with fuel switching. Expansion of the natural gas network is also consistent with the longer term ambitions of reducing EU greenhouse gas emissions by 2050 by over 80% (European Commission, 2011), as longer term ambitions to inject biomethane into the natural gas network has the potential to reduce emissions by 74% compared to natural gas (O'Shea et al., 2017).

To fully examine the factors influencing the choice of home-heating system, we would ideally have had access to individual household level data, as even aggregating to Small-Area level can mask important heterogeneity. Also, aside from the network roll-out data, we only have data for one point in time. A panel dataset on how gas proportions and various characteristics change over time, would have given us greater ability to identify effects. Similarly, the inclusion of other spatially coded information, such as relative prices of alternate fuels, or the location of kerosene suppliers, for example, would have significantly benefited this paper. These are all limitations of the research. However, our ability to examine time-trends in adoption is quite novel and makes a unique contribution to the wider fuel switching literature.

Disclaimer

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Appendix A.

A.1. Descriptive statistics for all variables included in estimations

Table A1
Descriptive statistics.

Variable category	Variable	Obs	Mean	Std. Dev.	Min	Max
Gas variables	Gas	9638	0.565	0.328	0	1
	Max length years	9638	14.523	13.134	0	111
	log(mean distance to gas network)	9638	3.252	1.074	0.732	6.906
Peat proximity	log(distance to bkt bog)	9638	8.772	1.167	−3.037	10.638
	log(distance to cut bog)	9,638	9.315	0.639	6.147	10.786
Coalban areas	Coalban dummy	9638	0.829	0.377	0	1
Density	Household count	9638	94.853	22.256	21	252
	Area km	9638	3.691	13.026	0.0163	417.358
Socioeconomic	EconWorking	9638	0.516	0.141	0	0.942
	EconLooking for first job	9638	0.010	0.012	0	0.489
	EconUnemployed	9638	0.110	0.064	0	0.440
	EconStudent	9638	0.117	0.083	0	0.980
	EconHome	9638	0.084	0.036	0	0.297
	EconRetired	9638	0.116	0.090	0	0.727
	EconDisabled	9638	0.042	0.037	0	0.494
	EconOther	9638	0.003	0.016	0	0.595
	Age 0–14	9638	0.195	0.090	0	0.594
	Age 15–24	9638	0.353	0.140	0	0.873
	Age 25–44	9638	0.133	0.077	0	0.987
	Age 45–64	9638	0.209	0.090	0	0.662
	Age 65 plus	9638	0.110	0.094	0	0.780
	EduPrimary	9638	0.128	0.109	0	0.722
	EduSecondary	9638	0.344	0.105	0	1
	EduTechnical	9638	0.183	0.063	0	0.5
	EduDegreeplus	9638	0.296	0.179	0	1
	EduRefused	9638	0.049	0.054	0	1
	TenOwnmortgage	9638	0.347	0.192	0	0.953
	TenOwnnomortgage	9638	0.275	0.196	0	0.808
	TenRentland	9638	0.249	0.215	0	0.985
	TenRentlocal	9638	0.091	0.165	0	0.987
	TenRenvol	9638	0.011	0.043	0	0.688
	TenRentfree	9638	0.011	0.020	0	0.890
Dwelling	DwellBungalow	9638	0.798	0.292	0	1
	DwellFlat	9638	0.176	0.280	0	1
	DwellBedsit	9638	0.006	0.025	0	0.746
	DwellOther	9638	0.021	0.031	0	0.982
	Proportion EFG	9638	0.326	0.292	0	1
	Age Pre 1945	9638	0.138	0.221	0	0.988
	Age 1945–60	9638	0.088	0.171	0	0.954
	Age 1960–80	9638	0.214	0.275	0	1
	Age 1980–2000	9638	0.247	0.268	0	0.990
	Age Post 2006	9638	0.248	0.318	0	1

A.2. Results from first stage supply equation

Table B1
First stage supply equation.

Dep Var: max length in years since network in place				
Variable	Linear		Quadratic	
	Coefficient	Robust SE	Coefficient	Robust SE
Household count	0.102***	(0.028)	6.332***	(1.790)
Household count sq	−0.000**	(0.000)	−0.022***	(0.008)
Areakm	0.162***	(0.016)	2.773**	(1.079)
Areakm sq	−0.000***	(0.000)	−0.000**	(0.000)
log(distance to cut bog)	0.972***	(0.087)	44.660***	(6.365)
log(distance to bkt bog)	0.399***	(0.140)	8.285	(10.992)
log(mean distance to gas network)	−3.899***	(0.129)	−91.128***	(9.847)
Coalban dummy	2.319***	(0.216)	98.124***	(15.353)
EconWorking	**[REF]**		**[REF]**	
EconLooking for first job	−6.700	(16.052)	−181.729	(1166.800)
EconUnemployed	−7.628**	(3.704)	−542.257*	(301.803)
EconStudent	−6.209	(4.497)	−423.807	(359.568)
EconHome	9.683*	(5.359)	382.041	(442.248)
EconRetired	−4.277	(6.972)	−708.001	(560.839)
EconDisabled	2.635	(5.257)	−614.494	(413.031)
EconOther	9.977	(8.273)	241.815	(686.109)
Age 25–44	**[REF]**		**[REF]**	
Age 0–14	3.929	(3.868)	23.942	(331.530)
Age 15–24	16.346***	(5.366)	706.930	(430.658)
Age 45–64	6.820**	(3.219)	−2.660	(269.857)
Age 65 plus	14.968**	(7.520)	1291.967**	(639.143)
EduSecondary	**[REF]**		**[REF]**	
EduPrimary	−2.259	(2.866)	−147.458	(237.319)
EduTechnical	−5.784*	(3.271)	−331.153	(264.163)
EduDegreeplus	5.392***	(1.917)	283.807*	(158.999)
EduRefused	9.252**	(3.887)	589.154*	(338.634)
TenOwnmortgage	**[REF]**		**[REF]**	
TenOwnnomortgage	−0.600	(2.191)	−45.547	(184.580)
TenRentland	2.843**	(1.381)	90.053	(114.931)
TenRentlocal	3.347**	(1.415)	279.572**	(113.928)
TenRenvol	0.160	(2.666)	93.094	(202.774)
TenRentfree	11.902*	(6.710)	321.387	(517.277)
DwellHouse	**[REF]**		**[REF]**	
DwellFlat	0.513	(0.859)	21.788	(72.837)
DwellBedsit	8.401	(10.856)	1315.792	(1011.618)
DwellOther	8.870*	(4.635)	151.917	(369.691)
Proportion EFG	0.160	(1.163)	66.561	(95.703)
AgePost2000	**[REF]**		**[REF]**	
AgePre1945	9.851***	(1.721)	652.140***	(145.094)
Age 1945–60	4.592***	(1.577)	359.113***	(125.876)
Age 1960–80	5.355***	(0.943)	227.464***	(76.441)
Age 1980–2000	6.254***	(0.615)	235.929***	(48.380)
Constant	−5.484*	(3.266)	−662.089**	(262.435)
N	9638		9638	
Weak id (Kleibergen–Paap rk Wald F)[a]	63.2		7.72	
Weak id (Kleibergen–Paap rk Wald F)[b]	95.18		20.73	
Underid (Kleibergen–Paap rk LM)a	0.001		0.001	
Underid (Kleibergen–Paap rk LM)b	203.642		30.82	

Notes: Results from IV-GMM specification. Cluster-robust standard errors in parenthesis.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.
[a] Linear and quadratic first stage estimated jointly.
[b] Linear and quadratic first stage estimated separately.

A.3. Robustness and sensitivity analysis

Table C1
Results of alternative specifications.

Variable	(1)	(2)	(3)	(4)
Maxlengthyears hat	0.030***	0.028***	0.030***	0.031***
Maxlengthyears squared hat	−0.000***	−0.000***	−0.001***	−0.001***
log(distance to cut bog)	0.014***	0.019***	0.014	0.018***
log(distance to bkt bog)	−0.007*	−0.010***	−0.013	−0.007
log(mean distance to gas network)	−0.115***	−0.132***	−0.119***	−0.120***
Coalban dummy	0.051***	0.066***	0.055**	0.062***
EconWorking	**[REF]**		**[REF]**	**[REF]**
EconLooking for first job	−0.258		−0.312	−0.333
EconUnemployed	−0.342***		−0.380*	−0.417***
EconStudent	−0.344***		−0.359**	−0.413***
EconHome	−0.334***		−0.282	−0.326*
EconRetired	−0.665***		−0.671***	−0.758***
EconDisabled	−0.598***		−0.512***	−0.700***
EconOther	−0.173		−0.071	−0.147
Age 25–44				
Age 0–14	0.568***		0.493*	0.585***
Age 15–24	0.122		0.176	0.203
Age 45–64	−0.269***		−0.283*	−0.273**
Age 65 plus	0.878***		1.002***	1.026***
EduSecondary	**[REF]**		**[REF]**	**[REF]**
EduPrimary	0.207***		0.099	0.198*
EduTechnical	−0.076		−0.130	−0.117
EduDegreeplus	0.224***		0.216**	0.243***
EduRefused	−0.090		−0.020	−0.046
TenOwnmortgage				
TenOwnnomortgage	−0.350***		−0.304***	−0.347***
TenRentland	−0.156***		−0.086	−0.151***
TenRentlocal	0.079**		0.164**	0.110**
TenRenvol	−0.038		−0.001	−0.009
TenRentfree	−0.263*		−0.220	−0.251
DwellBungalow	**[REF]**	**[REF]**	**[REF]**	**[REF]**
DwellFlat	−0.223***	−0.275***	−0.277***	−0.219***
DwellBedsit	−0.415**	−0.550***	−0.290	−0.259
DwellOther	−0.322***	−0.443***	−0.426***	−0.327**
Proportion EFG	−0.505***	−0.569***	−0.477***	−0.496***
AgePost2006	**[REF]**	**[REF]**	**[REF]**	**[REF]**
AgePre1945	0.360***	0.177***	0.399***	0.422***
Age 1945–60	0.312***	0.116***	0.307***	0.348***
Age 1960–80	−0.150***	−0.425***	−0.175***	−0.134***
Age 1980–2000	−0.149***	−0.271***	−0.148***	−0.133***
Deprivation index		0.009**		
Average employment compensation			0.359**	
Constant	0.880***	0.984***	0.608**	0.858***
N	9638	9642	9638	9638

Notes: Results from IV-GMM specification. Cluster-robust standard errors in parenthesis.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table C2
Sensitivity analysis on missing gas segment date identifiers.

Variable Percentage missing	(1) 0	(2) 5	(3) 10	(4) 20
Maxlengthyears hat	0.041***	0.038***	0.036***	0.035***
Maxlengthyears squared hat	−0.001**	−0.001***	−0.001***	−0.001***
log(distance to cut bog)	0.022***	0.021***	0.023***	0.022***
log(distance to bkt bog)	−0.016	−0.014*	−0.013	−0.014**
log(mean distance to gas network)	−0.115***	−0.114***	−0.117***	−0.116***
Coalban dummy	0.078***	0.075***	0.071***	0.063***
EconWorking	**[REF]**	**[REF]**	**[REF]**	**[REF]**
EconLooking for first job	−0.061	−0.012	0.104	0.016
EconUnemployed	−0.084	−0.100	−0.147	−0.237*
EconStudent	−0.073	−0.134	−0.171	−0.182
EconHome	−0.113	−0.088	−0.140	−0.159
EconRetired	−0.692	−0.938***	−0.891**	−0.643**
EconDisabled	−0.624*	−0.764***	−0.565**	−0.612***
EconOther	−0.218	−0.199	−0.275	−0.232
Age 25–44				
Age 0–14	−0.076	0.118	0.217	0.304*
Age 15–24	−0.125	−0.045	−0.016	−0.031
Age 45–64	−0.619***	−0.472***	−0.487***	−0.453***
Age 65 plus	0.595	1.044***	0.962**	0.796***
EduSecondary	**[REF]**	**[REF]**	**[REF]**	**[REF]**
EduPrimary	0.048	0.146	0.161	0.172
EduTechnical	−0.252	−0.177	−0.152	−0.169
EduDegreeplus	0.066	0.092	0.127	0.172**
EduRefused	−0.651***	−0.511***	−0.360**	−0.300**
TenOwnmortgage				
TenOwnnomortgage	−0.292***	−0.364***	−0.321***	−0.337***
TenRentland	−0.188**	−0.160**	−0.169**	−0.156***
TenRentlocal	0.084	0.020	0.014	0.044
TenRenvol	0.138	0.103	0.085	0.025
TenRentfree	0.158	−0.034	−0.015	−0.076
DwellBungalow	**[REF]**	**[REF]**	**[REF]**	**[REF]**
DwellFlat	−0.258***	−0.238***	−0.232***	−0.234***
DwellBedsit	−0.533	−0.600	−0.591	−0.619*
DwellOther	−0.554**	−0.471**	−0.312	−0.341**
Proportion EFG	−0.435***	−0.414***	−0.424***	−0.410***
AgePost2006	**[REF]**	**[REF]**	**[REF]**	**[REF]**
AgePre1945	0.444***	0.382***	0.379***	0.344***
Age 1945–60	0.344***	0.285***	0.301***	0.301***
Age 1960–80	−0.178***	−0.172***	−0.164***	−0.164***
Age 1980–2000	−0.190***	−0.217***	−0.188***	−0.194***
Constant	1.182***	1.066***	1.011***	0.982***
N	5072	5572	6215	7129

Notes: Results from IV-GMM specification. Cluster-robust standard errors in parenthesis.

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table C3
Sensitivity analysis on average distance from gas network.

Variable Distance from network	(1) 50 km	(2) 30 km	(3) 20 km	(4) 10 km	(5) 5 km	(6) 1 km
Maxlengthyears hat	−0.006	0.033***	0.052***	0.055***	0.060***	0.032***
Maxlengthyears squared hat	−0.000	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***
log(distance to cut bog)	0.023***	0.016***	0.016***	0.020***	0.024***	0.019***
log(distance to bkt bog)	−0.009***	−0.005	−0.008**	−0.006	−0.010	−0.006
log(mean distance to gas network)	−0.089***	−0.049***	−0.032**	−0.046***	−0.052***	−0.120***
Coalban dummy	0.158***	0.102***	0.088***	0.090***	0.072***	0.063***
EconWorking	**[REF]**	**[REF]**	**[REF]**	**[REF]**	**[REF]**	**[REF]**
EconLooking for first job	−0.273	−0.126	−0.063	−0.012	0.025	−0.289
EconUnemployed	−0.399***	−0.426***	−0.446***	−0.670***	−0.708***	−0.427***
EconStudent	−0.463***	−0.481***	−0.494***	−0.570***	−0.515**	−0.398***
EconHome	−0.323***	−0.382***	−0.367**	−0.362	−0.449	−0.303*
EconRetired	−0.835***	−1.093***	−1.244***	−1.488***	−1.345***	−0.774***
EconDisabled	−0.547***	−0.923***	−1.183***	−1.449***	−1.426***	−0.710***
EconOther	0.053	−0.068	−0.140	−0.353	−0.349	−0.150
Age 25–44						
Age 0–14	0.449***	0.356***	0.231	0.325	0.438*	0.560***
Age 15–24	0.225**	0.118	0.060	0.191	0.162	0.188
Age 45–64	−0.117	−0.351***	−0.518***	−0.603***	−0.578***	−0.293***
Age 65 plus	0.977***	1.224***	1.387***	1.584***	1.540***	1.046***
EduSecondary	**[REF]**	**[REF]**	**[REF]**	**[REF]**	**[REF]**	**[REF]**
EduPrimary	0.314***	0.287***	0.282***	0.266*	0.219	0.187**
EduTechnical	−0.227***	−0.230***	−0.293***	−0.315*	−0.240	−0.124
EduDegreeplus	0.202***	0.244***	0.251***	0.270***	0.279**	0.253***
EduRefused	0.042	0.015	−0.009	0.084	0.107	−0.029
TenOwnmortgage						
TenOwnnomortgage	−0.291***	−0.312***	−0.345***	−0.307***	−0.316**	−0.351***
TenRentland	−0.099***	−0.147***	−0.179***	−0.218***	−0.209**	−0.153***
TenRentlocal	0.181***	0.199***	0.197***	0.256***	0.262**	0.119**
TenRenvol	−0.015	0.046	0.085	0.085	0.076	−0.009
TenRentfree	−0.349***	−0.496***	−0.562***	−0.501*	−0.498	−0.252
DwellBungalow	**[REF]**	**[REF]**	**[REF]**	**[REF]**	**[REF]**	**[REF]**
DwellFlat	−0.225***	−0.226***	−0.248***	−0.224***	−0.206***	−0.219***
DwellBedsit	−0.402*	0.130	0.527	0.825	0.739	−0.192
DwellOther	−0.060	−0.312**	−0.449***	−0.464**	−0.470*	−0.317**
Proportion EFG	−0.422***	−0.383***	−0.345***	−0.362***	−0.403***	−0.499***
AgePost2006	**[REF]**	**[REF]**	**[REF]**	**[REF]**	**[REF]**	**[REF]**
AgePre1945	0.462***	0.488***	0.498***	0.671***	0.702***	0.446***
Age 1945–60	0.347***	0.413***	0.439***	0.515***	0.539***	0.363***
Age 1960–80	−0.068***	−0.098**	−0.120**	−0.078	−0.073	−0.126***
Age 1980–2000	−0.058**	−0.113***	−0.139***	−0.106**	−0.107*	−0.126***
Constant	0.933***	0.690***	0.658***	0.647***	0.591***	0.840***
N	16,626	15,250	14,171	12,346	10,936	9638

Notes: Results from IV-GMM specification. Cluster-robust standard errors in parenthesis.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

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