Price elasticity of residential natural gas demand: Evidence from population microdata in Ireland

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Price Elasticity of Residential Natural Gas Demand: Evidence from Population Microdata in Ireland

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Abstract

This paper quantifies the short-run price elasticity of demand for residential natural gas consumption. We use a novel population dataset of natural gas consumption covering all residential consumers connected to the Irish natural gas network. We match retail prices to residential consumers using a representative profile of tariffs. Using supply area information, we match households to geo-referenced weather station data to control for weather effects. Our findings reveal a short-run elasticity ranging from -0.19 to -0.33. We explore heterogeneity in this effect across regions and household characteristics, finding variation in price response by house type, house size, consumer supply area and consumer meter type.

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1 Introduction

This paper estimates the short-run price elasticity of residential natural gas demand in Ireland. We use novel population microdata covering metered gas consumption for all Irish residential consumers for the period 2018 to 2023. These data are matched to period and supplier-specific retail gas prices. Our empirical strategy leverages within-household variation in domestic gas consumption over time, whilst also controlling for time period fixed effects. Dutch TTF wholesale gas prices are used as an instrument for retail gas prices, whilst regional variation in consumption patterns and weather are also accounted for. We find a short-run elasticity ranging from -0.19 to -0.33. The result indicates that Irish consumers are highly inelastic in the short-run with little ability for substitution. Heterogeneity analysis reveals variation in demand response across house types, with detached homes exhibiting more elastic consumption patterns. We also observe greater average demand elasticity among homes with more bedrooms. The data also suggests regional variation in price response across different consumer supply areas and slight variation in elasticities between prepay and non-prepay consumers.

Short-run price elasticity estimates are crucial for regulators and utilities, particularly when responding to supply shocks: it helps determine whether to use price or non-price interventions and how large they should be. This has become more important since Russia's invasion of Ukraine, which tightened gas supplies and increased price volatility, prompting European and national demand-reduction policies (see Schill et al., 2025). Elasticity estimates also inform operational and welfare analysis of levies and surcharges (e.g. carbon pricing, network cost recovery) and intermittent price changes. Such volatility arises due to fluctuations in both wholesale natural gas prices and regulated tariff components, such as network charges in Ireland and

Germany (Bundesnetzagentur, 2026; Commission for Regulation of Utilities (CRU), 2024) and price caps in the UK (Ofgem, 2026). These components vary by regulatory period. Estimating the welfare effects of these changes therefore requires short-run elasticity estimates.

This paper uses an instrumental variables identification strategy motivated by potential simultaneity bias. Observed prices and quantities consumed for traded goods are outcomes of a system of equations that form a simultaneously-determined equilibrium. This concern is present in the market for natural gas,where retail prices adjust to market conditions and are simultaneously determined with consumption, leading to potential endogeneity in price elasticity estimates. Following the precedent in the literature (Auffhammer & Rubin, 2018; Favero & Grossi, 2023; Frondel et al., 2019), we employ an instrumental variables approach, where wholesale gas prices serve as an instrument for retail prices, to address the simultaneity problem.

In addition, the richness of the population data used in this paper adds significant novelty to its results. Much of the existing literature relies on samples that are either spatially aggregated (e.g. country- or region-level panels) or based on small household samples, and therefore must aggregate consumption data across locations and time (Asche et al., 2008; Erias & Iglesias, 2022; Kostakis et al., 2021; Zeng et al., 2018). As a result, identification in these studies typically relies on variation across regions, time, or consumers, and estimates are often obtained from samples that may not be representative of the full population. In contrast, this paper exploits a population-level administrative dataset covering all residential gas consumers in the country, observed at each billing period between 2018 and 2023. The size and completeness of the dataset used in this paper enables a more precise estimation of short-run price elasticities and allows for robust analysis of heterogeneity across households. While some temporal and spatial misalignment between consumption and prices remains unavoidable due to variation in consumer billing periods, the population coverage ensures that estimates are broadly representative of economy-wide consumer responses.

This paper adds to the literature providing microdata-based estimates of residential price elasticity for natural gas, contributing estimates in an Irish context to complement existing case studies for Italy, Germany, Greece, Portugal and other European countries (see e.g., Asche et al., 2008; Favero & Grossi, 2023; Frondel et al., 2019; Kostakis et al., 2021, for European examples). In contrast to much of this literature, which relies on aggregated regional panels or survey-based samples and employs dynamic panel techniques to estimate long-run elasticities, our analysis sits squarely within the short-run elasticity literature and focuses on household demand responses when capital stock and appliance choices are fixed. Many of the aforementioned microdata-based case studies occur prior to the energy price shock following Russia's invasion of Ukraine. Our analysis covers the 2018-2023 period and thus covers extreme volatility in wholesale and retail gas prices seen at this time. This allows us to estimate the short-run demand responses in this extreme volatility. It is these factors, when combined with the richness of the microdata, that allows for robust estimations of Irish price elasticities of gas demand.

The remainder of the paper is organized as follows: Section 2 outlines the existing evidence on price elasticities in residential gas markets. Section 3 describes the data, including the sources for information on residential gas consumption, retail gas prices, wholesale gas prices and regional weather. Section 4 motivates our empirical framework and provides further justification for the instrumental variables approach. Section 5 outlines and discusses the empirical results. The paper concludes in Section 6 with a discussion of the economic and policy implications.

2 Literature

This section reviews the literature relating to the price elasticity of demand for natural gas among residential consumers, highlighting the contribution made by this paper. Research in this field may be disaggregated according to analyses of short and long-run price elasticities of demand. Methods and findings differ between these two contexts. Estimates of long-run price elasticities tend to employ dynamic panel models to elicit long-term trends. Papers estimating short-run price elasticities use a variety of panel methods, with a more recent body of literature employing quasi-experimental techniques to overcome issues of endogeneity. This paper contributes towards the latter strand of analysis, leveraging within-household variation in domestic gas consumption over time, while controlling for aggregate time effects. Endogeneity is addressed through an instrumental variables framework. We contribute to this literature by leveraging novel population microdata that contains natural gas billing information for all final residential users in the country between 2018 and 2023.

To summarise the literature, Table 1 shows a selection of pertinent estimates of both long and short-run price elasticities of demand. Asche et al. (2008) and Erias and Iglesias (2022) are representative of long run estimates, with a number of trends emerging. First, these papers most often employ dynamic panel or Autoregressive Distributed Lag (ARDL)-type methods. Second, long run price elasticities are commonly found to be on the more elastic end of the spectrum. This is in line with expectations, as capital stock is not fixed in the long run and one would expect estimates to be more elastic.

Asche et al. (2008) use dynamic panel data model specifications where lagged consumption is incorporated to capture adjustment behaviour between time periods. This is used to estimate residential gas demand for 12 European countries. Long-run

Table 1: Selected estimates of the price elasticity of demand for natural gas among residential consumers

Authors	Period	SR or LR	Technique	SR Elasticity	LR Elasticity
Alberini et al. (2020)	1997-2007	SR	Panel	−0.16	
Asche et al. (2008)	1978-2002	SR & LR	Dynamic panel	−0.24	0 to − 0.7
Auffhammer and Rubin (2018)	2004-2014	SR	IV w/ RDD	−0.23 to − 0.17	
Bianco et al. (2014)	1990-2012	LR	ARDL	−0.20	
Erias and Iglesias (2022)	2005-2020	SR & LR	ARDL	−0.14 to − 0.31	0 to − 0.64
Favero and Grossi (2023)	2016-2018	SR & LR	(Dynamic) Panel w/IV	−0.23 to − 0.51	
Frondel et al. (2019)	2006-2014	SR & LR	(Dynamic) panel w/ IV	−0.44	−0.66
Kostakis et al. (2021)	2012-2019	SR & LR	(Dynamic) Panel w/IV	−0.54 to −0.65	−0.78
Zhu et al. (2018)	1990-2017	SR & LR	Meta analysis	−0.23	
Zeng et al. (2018)	2018	SR	IV w/ Quantile Reg.	−0.90	

Note: Asche et al. (2008) estimate own price elasticities for a range of European countries. The Europe-wide estimate is -1.4, whilst the country-specific estimates are in the range of 0 to -0.7. The latter is reported in this table. SR = Short-run, LR = Long-run.

own price elasticities are in the range of -1.54, with a 'shrinkage estimator' providing insight into heterogeneity between countries. Asche et al. (2008) find evidence to suggest that there are structural differences in gas demand between countries. Similar structural differences are found by Erias and Iglesias (2022), who similarly examine price elasticity across a range of European countries, using an ARDL modelling framework. They consider price elasticities in both the short and long run, with long run estimates ranging from 0 to -0.641.

Many of the estimates of long run elasticities use dynamic panel data models. While accounting for unobserved individual-level fixed effects, the simultaneity of demand and supply in the setting of prices must also be accounted for. Simultaneity is the primary endogeneity concern in this literature; prices are determined by the coincidence of demand and supply and are therefore potentially endogenous. Indeed, this is an issue highlighted by Auffhammer and Rubin (2018) and others (e.g., Zeng et al., 2018) as being an area of concern for many analyses in the literature. Some dynamic papers have employed instrumental variables to overcome issues of endogeneity. For example, Frondel et al. (2019) employ a dynamic panel estimator to estimate the short and long-run price elasticity of natural gas demand in Germany. This is used alongside the sum of the regulated price components, such as grid fees, taxes, and levies, as an instrument to cope with the likely endogeneity of electricity prices. They find short- and long-run price elasticities of -0.44 and -0.66, respectively.

A similar empirical strategy is adopted by Kostakis et al. (2021) who use both static and dynamic panel data techniques to estimate price elasticity of demand for natural gas, employing lagged prices for gas and a related commodity, oil, as an instrument to control for unobserved heterogeneity. The estimated value of the short-run own-price elasticity ranges from -0.82 to -0.90 (-0.86 on average) and is higher in relation to those of the static model. The estimated long-run price elasticity ranges from -0.93 to -1.01 (-0.98 on average). Cross price elasticities and the influence of sociodemographic variables are also estimated. However, the use of lagged variables as an instrument is not without difficulty. Tiedemann et al. (2023) show that using a lagged endogenous variable may be subject to bias if there is autocorrelation.

The estimation of short-run elasticities allows for greater use of quasi-experimental techniques in the estimation of price elasticity of gas demand, and it is in this part of the literature that this paper situates itself. Auffhammer and Rubin (2018) are amongst the first to consider this in the context of US gas demand, exploiting exogenous temporal and spatial variation in prices, using geographical market discontinuities. In addition, an instrumental variables strategy is employed, using wholesale natural gas spot prices. They find that the elasticity of demand for residential natural gas is between -0.17 and -0.23 and provide evidence of significant seasonal and income-based heterogeneity in this elasticity.

In a similar vein, Favero and Grossi (2023) examine the price elasticity of demand for gas in Italy. Fixed and random effects are used to account for household-level unobserved heterogeneity. To overcome endogeneity, they employ two instrumental variable models; first, they use monthly mean wholesale natural gas prices. This is correlated with the retail price but does not affect demand except through retail price variation. Second, they consider changes in regulated price components. These are uncorrelated with demand as they are set exogenously by the market regulator. Zeng et al. (2018) also take an instrumental variables approach, using non-residential natural gas as an instrument for residential natural gas prices.

This paper contributes to the literature on quasi-experimental estimation of short run price elasticities, providing insight using Irish data. This is the first such application in an Irish context, contributing towards this literature estimating short-run price elasticities using rich microdata sources. Related literature generally uses dynamic methods in examining related aspects of natural gas demand. Harold et al. (2015) and Harold et al. (2018) examine the determinants of natural gas demand using data from a field experiment. Price effects are excluded from these analyses; no intra-household price variation was observed during the experimental period. Curtis and Stanley (2016) use an error correction modelling framework to recover short-run elasticities of -0.25. This research is focused on the period 1970 - 2013 and does not employ a population dataset. As previously discussed, Asche et al. (2008) analysed a sample of European level countries, which includes Ireland. Asche et al. (2008) estimates do not account for simultaneity bias. In addition, their analysis is of aggregated data, as opposed to a quasi-experimental analysis of household microdata.

Indeed, the issue of aggregated vs. micro data raises an important point to note. A range of methodologies have been employed to analyse the price elasticity of gas demand, from ARDL-type approaches of aggregated data (Asche et al., 2008), to quasi-experimental analyses of household-level microdata (Auffhammer & Rubin, 2018; Favero & Grossi, 2023). Meta analyses have shown that the form of the data can influence the magnitude of the elasticity coefficient, an important consideration when interpreting findings. Zhu et al. (2018) find that price elasticity estimates are sensitive to the time interval of analysis and the micro or macro resolution of the data. The latter is a conclusion shared by Halvorsen and Larsen (2013). This research finds that price elasticity estimates from macro data, or aggregated microdata, are often lower in absolute terms than those estimated using microdata. This is due to assumed homogeneity of consumer preferences and prices.

From this review, it is clear that there is a shift from the estimation of dynamic panel, long run estimates to the use of quasi-experimental techniques in the estimation of short-run estimates. The growing availability of large micro-datasets provides a platform for the use of quasi-experimental techniques to overcome many endogeneity concerns. This paper builds on the recent trend, instigated by Auffhammer and Rubin (2018), and followed by in analyses of Favero and Grossi (2023) and Frondel et al. (2019) to employ quasi-experimental panel data techniques to estimate the short run price elasticity of demand for residential gas demand. We use an Irish setting, where data are available for the national population.

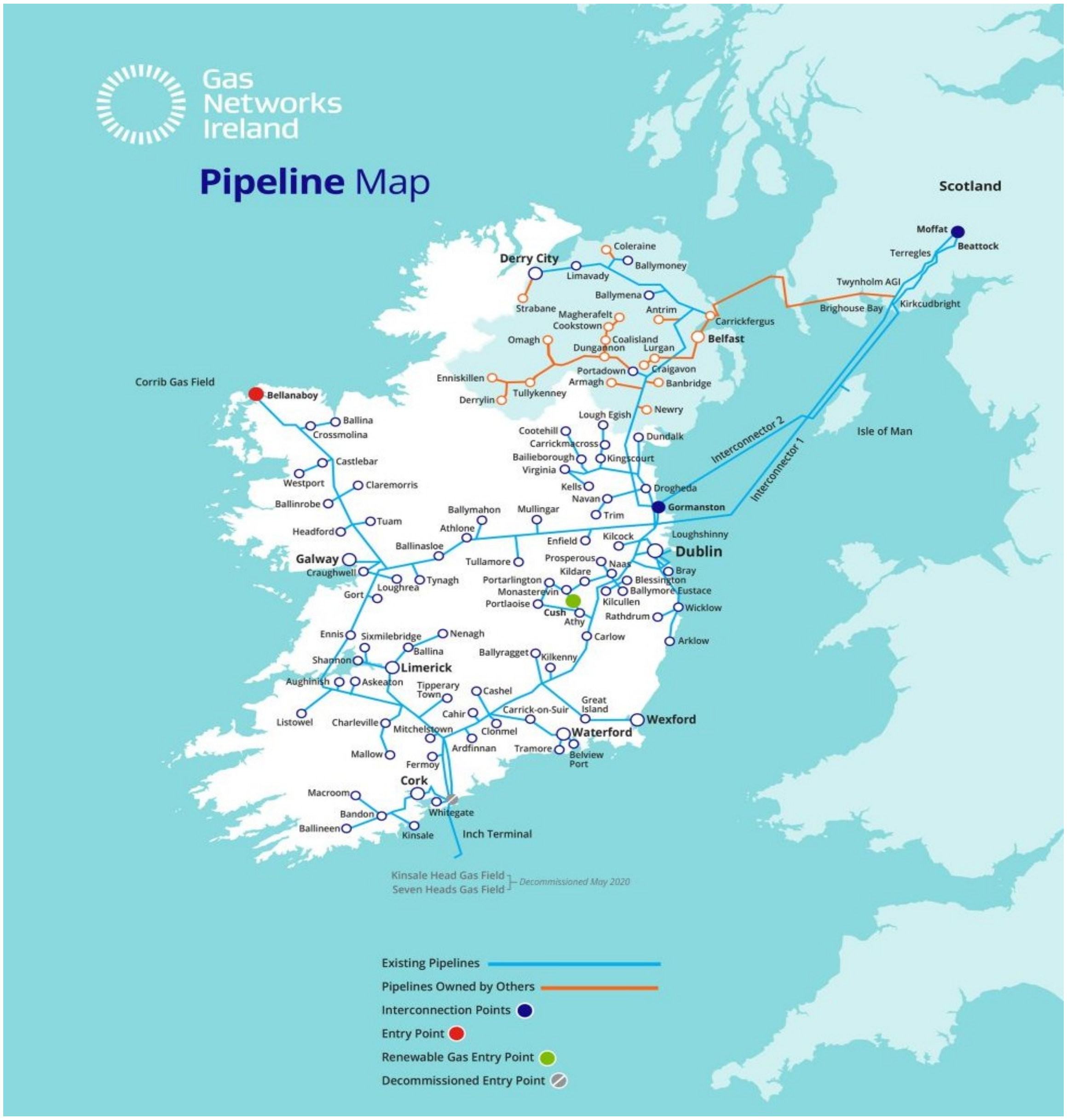
3 Data

This paper utilises a population dataset documenting the natural gas consumption of all residential consumers connected to the Irish natural gas network. This is combined with data on meteorological conditions, retail prices and wholesale prices. Gas consumption data are sourced from the gas network operator, Gas Networks Ireland (GNI) and span a six-year period from January 2018 to December 2023. Several global shocks known to have significantly impacted energy prices occurred during this time, including the COVID-19 pandemic and the energy crisis prompted by the Russian invasion of Ukraine. We exploit exogenous variation in wholesale energy prices induced by these global shocks to identify the effect of price variation in our analysis.

Figure 1 shows the network topography, giving insight into the spatial distribution of consumers in our dataset. The population of natural gas consumers is limited to those in the hinterland of the main population centres of Dublin, Cork and Galway, with linkages to other county towns such as Castlebar and Athlone. Those living along the interconnecting routes also have access to networked natural gas.

The metered gas consumption data sourced from the gas network operator does not contain information on the concurrent tariff faced by each consumer; this is commercial information only available to the supplier. We must match these consump-

Figure 1: GNI Gas Pipeline Network



Source: Gas Networks Ireland (GNI)

tion data with data on representative retail prices to estimate the price elasticity of demand. We also match our consumption data with data on representative international wholesale gas prices, which serve as our instrument, using Dutch TTF day-ahead spot prices sourced from the European Energy Exchange. In addition, we control for weather conditions using data from the Irish Meteorological service, Met Éireann. Each of these datasets and their use in the analysis will now be outlined in turn.

3.1 Natural gas consumption data

Gas Networks Ireland, the Irish gas network operator, have provided meter reading data for all consumers connected to the Irish natural gas network for a six-year period from January 2018 to December 2023. The gas consumption data is a rich profile of consumption patterns, where all actual recorded meter readings are included. When an actual reading is unavailable, the network operator replaces the missing value with an estimate. Our analysis uses only actual meter readings and excludes all estimated values. As these data are sourced directly from the network operator, sociodemographic information is limited, however a number of variables are present to aid the analysis. These include retail supplier, supply area location (see Figure 1), each consumer's dwelling type and the number of bedrooms in the dwelling.

For residential consumers, the gross dataset totals 31.7 million observations. However, the raw data may be subject to a number of measurement issues related to metering practices, billing conventions, or administrative processes. Consumers with specific measurement issues are removed from the dataset (see Table 2), yielding a final sample of 27,576,674 observations across 576,951 households. This section proceeds in two steps. First, we describe the sample-selection and data-cleaning applied to address these issues. Second, we discuss the frequency of meter readings and resulting structure of the panel.

3.1.1 Data cleaning

We apply a series of data-cleaning measures to remove data that are suspected as potentially erroneous, testing the sensitivity of results to all such amendments. Each data cleaning measure addresses a specific source of noise that, if retained, could bias estimated price elasticities. The number of observations and households removed with each restriction is shown in Table 2. Each data cleaning measure and the motivation behind its implementaion will now be outlined.

First, households with non-positive consumption values are removed. Negative consumption values are unlikely to represent actual gas use and instead most likely indicate billing errors, meter malfunctions, or data entry anomalies.

Second, we exclude households that meet either of two extreme criteria. We exclude households for which the interval between meter readings falls at or above the 99th percentile of the distribution. Extremely long billing intervals suggest deviations from standard metering practices, such as delayed readings or account irregularities. We also exclude households whose daily consumption lies at or above the 99th percentile. These extreme values likely reflect data errors, atypical billing adjustments, or non-residential usage patterns rather than normal household demand behaviour. Any household with at least one observation meeting either of these criteria is dropped entirely to avoid potentially biasing the panel with distorted observations.

Finally, households with zero consumption values are necessarily excluded in specifications that rely on logarithmic transformations of consumption.

Similar data-cleaning strategies are common in the empirical energy-demand literature using billing or meter data, where researchers exclude extreme consumption values, irregular billing intervals, or non-positive usage to mitigate measurement error and institutional noise (see, e.g., Auffhammer and Rubin (2018), Borenstein and Davis (2012), Ito (2014), Frondel et al. (2019), Favero and Grossi (2023)). These studies highlight that such observations can induce attenuation bias or spurious price responses if retained.

To assess the sensitivity of our results to these data-cleaning restrictions, we re-estimate our preferred instrumental-variables specification after each restriction is applied sequentially, generating a specification curve across 22 intermediate samples. Figure 10 illustrates this pattern. Each point in Figure 10 represents the estimated elasticity under a given set of data-cleaning restrictions, each motivated by potential sources of measurement error or extreme observations. The observed clustering of estimates indicates that no single restriction drives the results. Where small shifts are observed, such as a modest increase in elasticity when extreme meter-reading intervals are retained, the direction of change is consistent with the expected upward bias of the measurement error.

Further details on the data cleaning and associated sample sizes are provided in Sections A.1 and A.2. After applying all data-cleaning restrictions, Table 2 shows that the final sample consists of 576,951 residential households and 27,576,674 household-period observations.

3.1.2 Meter types

The dataset comprises observations of both prepay and non-prepay meters, with meter reading intervals varying by meter type. Non-prepay meters comprise 91% of the population dataset and are read an average of once every 88 days, with an inter-quartile range of 52 days to 121 days. Consumers with prepay meters comprise 9% of our population dataset. These consumers have their consumption data recorded more frequently, with an average meter reading every 11 days. There are 9,011,588 observations from prepay meters and 18,565,086 observations from non-prepay meters. There are 523,955 households with non-prepay meters and 52,996 households with prepay meters in the dataset, for a total of 576,951 households. [1]

Table 2: Observations remaining after data cleaning.

	Obs Dropped	Obs Remaining	HH Dropped	HH Remaining
Full sample		31,699,892		710,866
Sample restrictions:				
Drop: HH where all consumption obs are zero	17,451	31,682,441	567	710,299
Drop: HH where some consumption obs are zero	212,651	31,469,790	6,907	703,392
Drop: Obs where consumption is in the 99th percentile	408,424	31,061,366	13,265	690,127
Drop: HH with only one obs across the 6-year period	2,712	31,058,654	88	690,039
Drop: Obs where days between meter readings is in the 99th percentile	318,779	30,739,875	10,353	679,686
Drop: HH where at least one consumption obs is in the 99th percentile	1,565,712	29,174,163	50,852	628,834
Drop: HH where at least one obs meter interval is in the 99th percentile	1,597,489	27,576,674	51,884	576,950
Final sample		**27,576,674**		**576,950**

Notes: Obs denotes observations. HH denotes households.

3.2 Retail price data

To estimate the price elasticity of demand, we require data on both consumption and prices. As the gas consumption dataset does not contain information on prices, each household is matched with a retail natural gas tariff using external data sources.

Tariffs vary primarily by time period and supplier. We match each household to a tariff according to supplier at the time of consumption, as these data are observed in the gas consumption dataset. There are additional tariff details unobserved in

[1] Prepay meters require advance payment for gas consumption, with usage deducted from purchased credit, whereas non-prepay meters bill households retrospectively based on metered consumption over a billing period.

the dataset. Suppliers can offer discounts for bundled electricity and gas plans. In addition, discounts are routinely given by Irish suppliers of electricity and gas for the first 12 months of a contract (Commission for Regulation of Utilities [CRU], 2023).[2] Additional unobserved discounts cannot be ruled out.

There is no centralised source of historical tariffs available in Ireland, and we must use a number of sources to assemble a profile of retail tariffs available throughout our sample period. Two primary sources of retail price data are used. First, we draw on a historical database collated by the Commission for the Regulation of Utilities (CRU), the Irish statutory body charged with overseeing the Irish energy and water sectors. These data were received through personal communication with the CRU and represent a databank of representative retail prices on the market for each natural gas supplier for the period of January 2019 to January 2022 and August 2022 to December 2023. We supplement the CRU-provided data with an historical price series recorded by a price comparison website, 'bonkers.ie'. This price series contains both unit charges and standing charges for all Irish suppliers between January 2020 and December 2023. This data is primarily used to provide price data for the period of January 2022 until July 2022 as there are no prices available in the CRU-provided data for this period. In short, we construct a representative profile of tariffs in the periods of January 2019 - January 2022 and August 2022 - December 2024 using the CRU-provided data and supplement the period of January 2022 - July 2022 using 'bonkers.ie'- provided data.

Since neither of the previous sources contains data for 2018, we supplement the dataset with information obtained from the Internet Archive's Wayback Machine. The Internet Archive is a digital archive that preserves time-stamped snapshots of

[2]For robustness, we test whether these discounts associated with supplier switching affect elasticities. To test, we isolate households where there is more than one supplier listed and run dummies for prices 12 months after the switch.

web pages, allowing access to historical pricing. We use this resource to recover suppliers' advertised unit and standing charges from archived versions of their official websites for 2018 and to cross-reference these figures against the CRU-reported unit and standing charges for 2019-2023.

For cross-referencing purposes, summary statistics by source and period for both unit charge and standing charge are presented in Tables 3 and 4. When looking to Tables 3 and 4, we see the frequency of each data for each defined time period where N refers to the number of unique monthly price data that exists in the given period. Some important trends emerge. We see that the mean and range of values is similar, regardless of source of retail price data. This gives us confidence in the data employed for our analysis. In addition, the summary statistics give insight into the between-time period range of retail prices experienced in Ireland.

For completeness, we estimate our baseline specification excluding all 2018 observations to assess whether the estimated price elasticity is influenced by the inclusion of Internet Archive-sourced prices. The results, reported in Table B.6, indicate that both the magnitude and statistical significance of the estimated elasticity are effectively unchanged across our preferred specifications, suggesting that the baseline findings are not driven by the inclusion of 2018 data. We also examine the robustness of the estimated price elasticity to alternative constructions of the retail price series. First, we re-estimate the preferred specification using each retail price source in isolation. Results of this test is shown in Table B.7. Across all specifications, the estimated elasticity remains negative, highly statistically significant, and qualitatively similar, ranging from –0.25 to –0.34, indicating that the results are not driven by any single price source.

Second, we assess sensitivity to the ordering of price-source preference used to construct the combined series. Using Bonkers.ie prices for 2020–2023, CRU prices for

2019, and Internet Archive prices for 2018 (Table B.8), we again obtain stable and statistically significant elasticity estimates. Taken together, these checks suggest that the main findings are robust to alternative price-series constructions.

Figure 2 plots the distribution of volumetric prices by supplier for the time period of this analysis. A number of observations emerge. First, between-supplier variation is relatively small; suppliers move in tandem and are close to the mean price. One supplier, Flogas, is a consistent outlier. Second, prices are relatively uniform for much of the duration with much variation occurring post February 2022, with the Russian invasion of Ukraine.Between 2023 and 2024, it appears that supplier unit charges remain relatively static, and we then see a moderate decline in the latter part of 2023. Overall, the evidence suggests that supplier pricing behaviour is strongly correlated, implying that suppliers likely respond to common market signals or shared cost determinants rather than adjusting prices independently. Having constructed a profile of tariffs by supplier and time period, we match these to each household in the gas consumption dataset using time period and supplier information contained therein.

The final step in the processing of retail price data relates to how one must incorporate the two-part nature of gas tariffs into the analysis. Networked gas in Ireland is priced using two-part tariffs; each residential consumer is charged a standing charge per day alongside a €/kWh volumetric charge. Controlling for two tariff elements in an econometric setting opens up the possibility of multicollinearity. To address this, we compute three supplier specific tariffs for each consumption interval: a marginal tariff; a consumption-weighted average price and; a time-weighted average price. We use each metric as regressor and find that our elasticity estimates are robust to each choice of tariff, indicating that the results are not sensitive to the specific method of tariff calculation. The results for our elasiticity estimates for the marginal tariff are

Table 3: Descriptive statistics for retail unit charges, by period

Panel A: Pre-Covid (Jan 2018–Mar 2020)

Price Source	N	Mean	SD	Min	Max
CRU price	15	0.067	0.002	0.065	0.071
Bonkers price	3	0.065	0.000	0.065	0.065
Internet Archive price	12	0.063	0.004	0.059	0.071

Panel B: Covid (Apr 2020–Jun 2021)

Price Source	N	Mean	SD	Min	Max
CRU price	15	0.061	0.002	0.058	0.067
Bonkers price	15	0.060	0.001	0.059	0.064
Internet Archive price	6	0.059	0.004	0.054	0.065

Panel C: Pre-Energy Crisis (Jul 2021–Dec 2021)

Price Source	N	Mean	SD	Min	Max
CRU price	6	0.070	0.007	0.062	0.078
Bonkers price	6	0.069	0.007	0.061	0.079
Internet Archive price	5	0.062	0.007	0.056	0.073

Panel D: Energy Crisis (Jan 2022– Dec 2023)

Price Source	N	Mean	SD	Min	Max
CRU price	18	0.147	0.015	0.112	0.157
Bonkers price	24	0.115	0.031	0.079	0.157
Internet Archive price	14	0.113	0.030	0.071	0.146

Notes: Period definitions:
Pre-Covid (2018–Feb 2020), Covid (Mar 2020–Jun 2021), Pre-Energy Crisis (Jul 2021–Dec 2021), Energy Crisis (2022–2023).
N in this instance refers to the number of unique monthly price data that exists in the period. The given summary statistics highlight the variation of each price data in a given period.

Table 4: Descriptive statistics for retail standing charges, by period

Panel A: Pre-Covid (Jan 2018–Mar 2020)

Price Source	N	Mean	SD	Min	Max
CRU price	15	0.271	0.047	0.231	0.331
Bonkers price	3	0.262	0.000	0.262	0.262
Internet Archive price	12	0.263	0.005	0.257	0.271

Panel B: Covid (Apr 2020–Jun 2021)

Price Source	N	Mean	SD	Min	Max
CRU price	15	0.241	0.017	0.226	0.270
Bonkers price	15	0.262	0.000	0.262	0.262
Internet Archive price	6	0.246	0.006	0.239	0.254

Panel C: Pre-Energy Crisis (Jul 2021–Dec 2021)

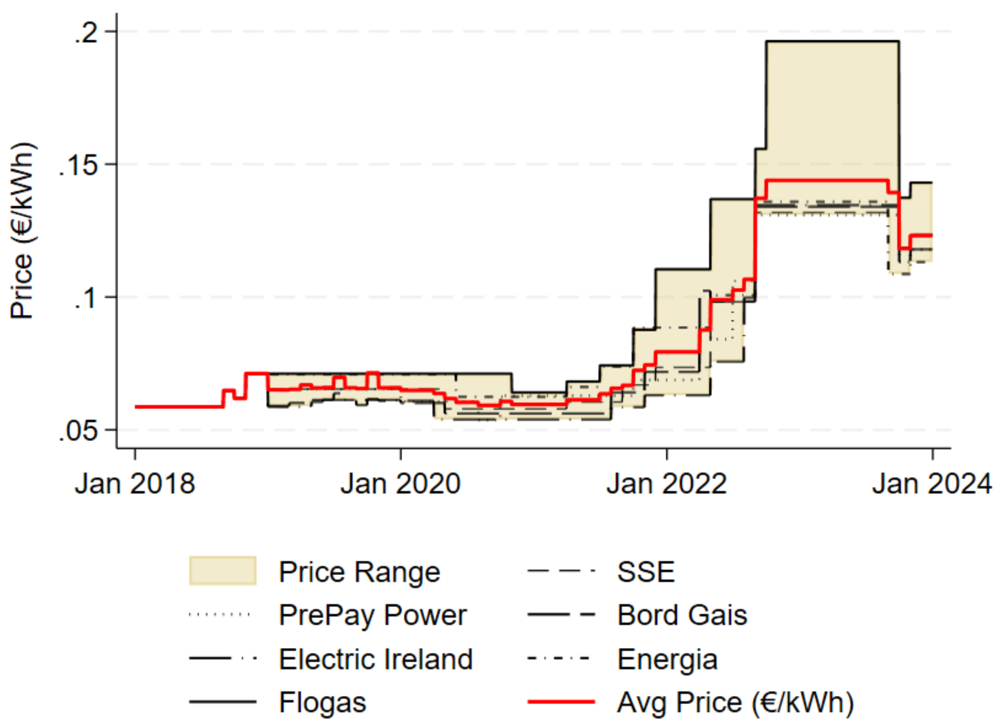
Price Source	N	Mean	SD	Min	Max
CRU price	6	0.308	0.030	0.280	0.359
Bonkers price	6	0.305	0.032	0.274	0.349
Internet Archive price	6	0.307	0.028	0.282	0.351

Panel D: Energy Crisis (Jan 2022–Dec 2023)

Price Source	N	Mean	SD	Min	Max
CRU price	18	0.393	0.020	0.357	0.404
Bonkers price	24	0.349	0.029	0.349	0.440
Internet Archive price	14	0.370	0.025	0.350	0.410

Notes: Period definitions are as follows: Pre-Covid (Jan 2018–Mar 2020), Covid (Apr 2020–Jun 2021), Pre-Energy Crisis (Jul 2021–Dec 2021), Energy Crisis (Jan 2022–Dec 2023). N refers to the number of unique monthly price data that exists in the period.The given summary statistics highlight the variation of each price data in a given period.

Figure 2: Retail gas unit prices by supplier (2018-2023)



shown in Table 6 while the results for our two average prices are shown in Table B.3 and Table B.4.

The calculation of each tariff type will now be outlined. First, the marginal tariff is the average supplier-specific €/kWh volumetric charge attributable to a given consumption window. The consumption-weighted average price is calculated as follows. For a consumption interval i comprising D days, the representative tariff for household h in interval i, $\bar{P}^C_{h,i}$, is calculated as a weighted average of the tariffs observed during that interval, with weights reflecting consumption during the interval. Formally, the consumption-weighted tariff may be defined as:

$$\bar{P}^C_{h,i} = \frac{\sum_{d=1}^{D} \left(P_d + \frac{S_d}{Q_d} \right)}{DB_i}, \tag{1}$$

where P_d is the volumetric price observed on day d, Q_d is the quantity of gas consumed on day d, and S_d is the standing charge for that day. This is then normalized by DB_i, the total number of days in the interval i. The final tariff, the time-weighted average price $\bar{P}^T_{h,i}$, is similar to the consumption-weighted average price, where the standing charge is weighted by number of days within the consumption interval:

$$\bar{P}^T_{h,i} = \frac{\sum_{d=1}^{D} \left(P_d + \frac{S_d}{DB_i} \right)}{DB_i}, \tag{2}$$

This variant treats the standing charge as evenly distributed across the interval, irrespective of daily consumption. These formulations are incorporated into our regression specifications for daily consumption, alongside heating degree days ($\ln hdd$) and quarterly time fixed effects. The tariff specifications outlined in equations (1) and (2) complement our primary specification to consider the impact changes to the standing charge may have on the consumption response. While we follow the standard assumption that consumers are responsive to marginal costs (Borenstein & Davis, 2012), we wish to consider whether consumers respond to average rather than marginal prices when facing non-linear price schedules (Ito, 2014).

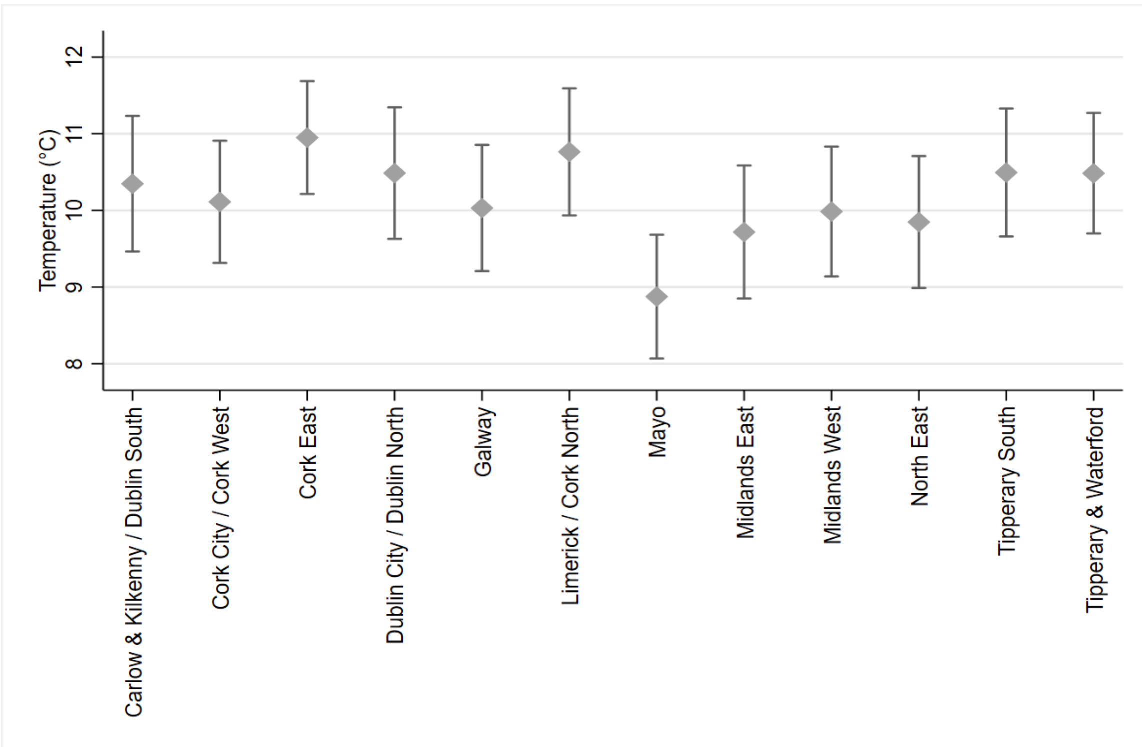
3.3 Weather data

We control for weather effects to account for otherwise unobserved heterogeneity. To do so, we link each consumer in our dataset with nearby weather station data. We optimise this spatial matching process using the following procedure. The gas consumption dataset contains information on supply area, with spatial supply areas summarised in Figure 4. As Figure 4 shows, supply areas are relatively large and the gas consumption data does not provide any finer spatial resolution on dwelling location. For each household located within a given supply area, we match the supply area centroid to a corresponding weather station using nearest-neighbour matching. In practice, we see minimal regional variation in temperature levels between regions. This is shown in Figure 3, which plots the mean temperature of each consumer supply area with it's associated 95% confidence interval. Given the expected spatial homogeneity of weather conditions within supply areas, any attenuation associated with this matching procedure is likely to be negligible. Figure 4 maps the nearest associated weather stations to each of the 15 gas supply areas.[3]

Having matched each consumer in the gas consumption dataset to an associated weather station, the next step is to construct a profile of the concurrent weather conditions. We follow convention in the literature by using a heating degree days (HDD) index to capture this (see e.g., Alberini et al., 2020; Auffhammer & Rubin, 2018; Favero & Grossi, 2023). This metric measures the demand for building heating,

[3] In Figure 4, the red dots represent weather stations and the green polygons represent consumer supply areas.

Figure 3: Mean Temperature with 95% Confidence Intervals by Supply Area



calculated as the difference between a base temperature and the observed average daily temperature. In our analysis, the base temperature is 15.5°C.[4] Positive HDD values indicate days when heating was likely required, with larger values representing colder conditions. For a billing period of length D_i days, the average daily HDD for household h in period i is computed as:

$$\mathrm{HDD}_{h,i} = \frac{1}{D_i} \sum_{d=1}^{D_i} \max(0, 15.5 - T_{h,i,d}), \tag{3}$$

where $T_{h,i,d}$ is the mean temperature on day d for the weather station associated with household h.

Dividing by the length of the billing period produces an average daily HDD, allowing for comparison across billing periods of different lengths and providing a measure of heating demand intensity per day.

3.4 Wholesale price data

We use wholesale natural gas prices as an instrument in our empirical strategy. Dutch TTF day-ahead spot prices are sourced from the European Energy Exchange. These price data are matched to each consumer in a similar way to retail pricing, by averaging daily wholesale prices over the length of the household's billing period. Formally, for household h with a billing period spanning D_h days, the average wholesale price assigned to that observation is

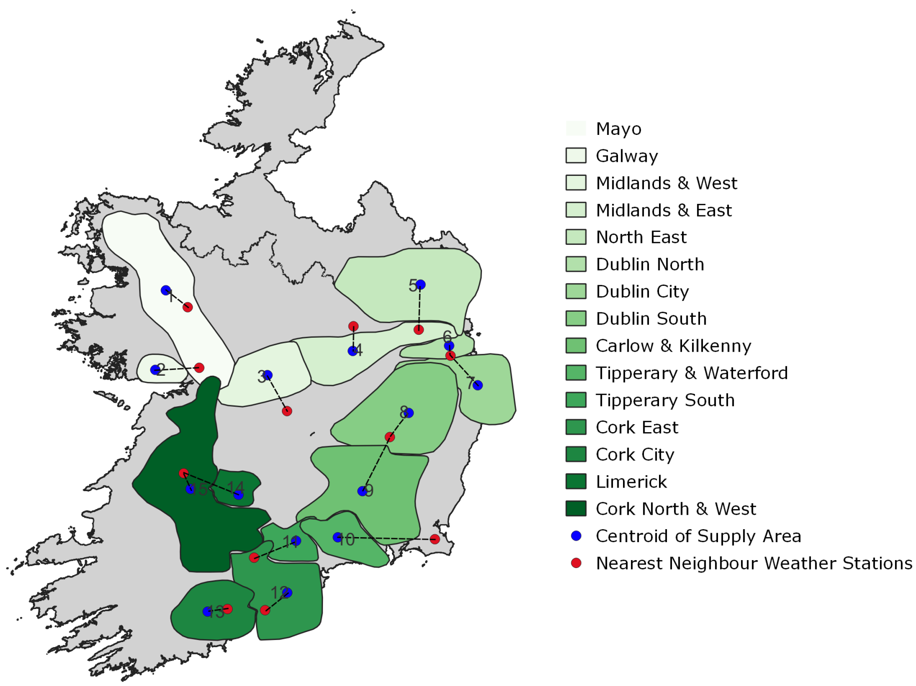
$$\mathrm{WP}_h = \frac{1}{D_h} \sum_{d=1}^{D_h} \mathrm{TTF}_d, \tag{4}$$

where TTF_d is the day-ahead TTF price on day d.

The European gas market is highly integrated, with prices in different regions often

[4] Hourly temperature data are aggregated to the daily level for HDD calculations.

Figure 4: GNI supply areas with associated nearest neighbour weather stations



moving together due to interconnected supply and demand dynamics. TTFDA prices are widely reported and transparent, providing reliable and timely data for use in 2SLS.

Figure 5: Average Irish retail vs Dutch TTF day-ahead gas prices between 2018–2024

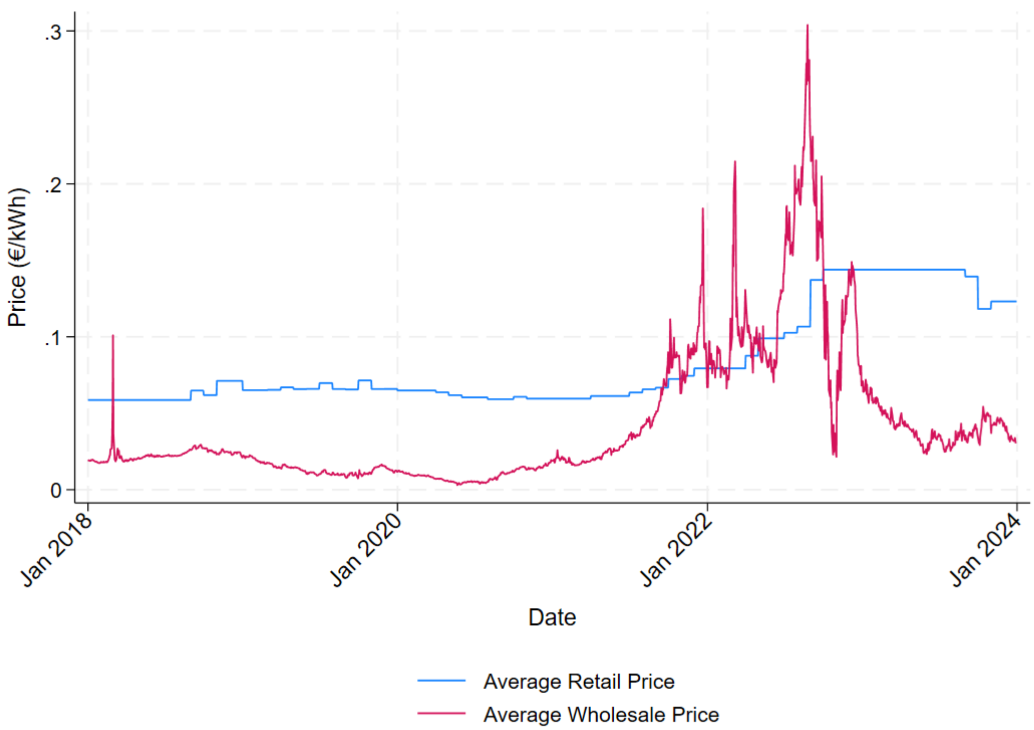


Figure 5 displays the relationship between TTF day-ahead wholesale natural gas prices and average Irish retail prices between 2018 and 2024. Over this period, retail prices closely track the broad trends in wholesale prices. Prior to 2021, retail prices remained relatively stable, with modest fluctuations corresponding to minor wholesale price movements. From early 2021 onwards, wholesale market volatility increased substantially, driven in part by global energy shocks and rising gas prices (Emiliozzi et al., 2025), and these shifts are mirrored in Irish retail tariffs. The largest retail price increases are observed during 2022, coinciding with peak TTFDA prices, suggesting a high degree of responsiveness of retail tariffs to wholesale cost signals during periods of market stress.

3.5 Descriptive statistics

Summary statistics for the analysis sample are reported in Table 5. Average daily household gas consumption is 34.5 kWh, with a relatively large standard deviation (27.5 kWh) and an extended right tail, reflecting significant heterogeneity in demand across households and billing periods. The distribution of daily consumption and logged daily consumption can be seen in Figure 6. Retail gas prices average €0.08/kWh, while wholesale spot prices are lower on average (€0.04/kWh) but display greater variability. Heating degree days, which provide a proxy for weather-driven heating demand for gas, average 215 per billing period. Household bedroom size ranges from 1 to 6. The average household contributes 148 observations (meter reading periods) to the dataset, with an average interval of 40 days between successive readings. Figure 7 shows the distribution of the number of days between consumer meter readings. We see bunching of readings taking place at 60 days, 120 days and 180 days. This pattern is consistent with meter readings being scheduled on fixed billing cycles rather than occurring continuously. In particular, the spikes at 60, 120, and 180 days likely reflect bi-monthly, quarterly, and semi-annual reading practices.

For daily consumption and heating degree days, the large within-household standard deviations seen in Table 5 indicate that most of the overall variation is driven by time-varying factors such as weather and seasonality rather than differences across households. Variables like bedrooms or meter-reading frequency have a within-household SD of zero, reflecting that these characteristics are fixed for each household. For

Table 5: Descriptive Statistics

Variable	Description	Mean	SD	SD (Within HH)	SD (Within HH + Quarter)	Min	Max
Daily Consumption	Daily household gas consumption per meter reading[1]	34.55	27.46	22.27	18.55	0.01	410.58
Retail gas price	Average household-specific retail gas price[2]	0.08	0.03	0.03	0.03	0.05	0.20
Standing charge	Fixed daily gas charge per household[2]	13.73	17.64	10.62	10.56	0.00	139.49
Wholesale gas price	TTF day-ahead wholesale gas price[3]	0.04	0.04	0.04	0.04	0.00	0.30
Heating degree days	Number of heating degree days during billing period[4]	215.83	303.96	218.92	203.55	0.00	2168.39
Bedrooms	Number of bedrooms per household	2.96	0.67	0.00	0.00	1	6
Meter reading frequency	Number of meter readings per household	148.75	126.98	0.00	0.00	1	1183
Days between readings	Days between consecutive meter readings[5]	40.15	49.03	28.99	28.79	1	263
Observations	27,576,674						

[1] Total household gas consumption divided by the number of days in the billing period (kWh/day).
[2] Measured in €/kWh.
[3] Dutch TTF day-ahead gas market price, measured in €/kWh.
[4] HDD calculated as $(15 - T_{mean})$ where $T_{mean} < 15°C$.
[5] Billing periods that start and end on the same day are recorded as 1 day.
[6] The GNI dataset also contains categorical indicators for gas supplier and supply area, which are used in the empirical analysis. Descriptive statistics on consumer supply areas can be found in Table C.1.Descriptive statistics on consumer suppliers are not reported to avoid disclosure of market shares.

prices, the high within-household SDs show that households experience substantial time-variation in both retail and wholesale gas prices over the sample period, which is essential for identifying price responsiveness in the panel. The variation in our control variables by region can be seen in Table C.1 of the appendix.

4 Methodology

As outlined in Section 3, our data consist of a household-level panel profiling natural gas consumption over a six-year period, matched with retail price, wholesale price and weather data. Gas consumption is measured according to meter readings gathered at irregular intervals. There are a number of confounding effects that must be considered in our empirical strategy. First, the irregularity of consumption windows must be accounted for, considering both the number of days in each consumption window and the fact that each day is not the same; a colder day will lead to higher expected gas consumption. We account for this by normalizing household consumption by the length of their consumption window. This accounts for both seasonal heterogeneity and irregular consumption window effects.

Second, we wish to control for time fixed effects, however, this is complicated given the presence of irregular consumption windows. We use a quarter-of-year fixed effect, calibrated according to the quarter during which the first day of a consumption window falls.By doing this, we account for seasonal heterogeneity.

A double-log specification forms our baseline model and is typically employed for the estimation of demand elasticities:

$$\ln Q_{i,t} = \beta_0 + \eta \ln \bar{P}_{i,t} + \gamma \ln HDD_{i,t} + \tau_t + \alpha_i + \epsilon_{i,t}, \tag{5}$$

Figure 6: Distribution of Daily Consumption and Logged Daily Consumption (2018–2023)

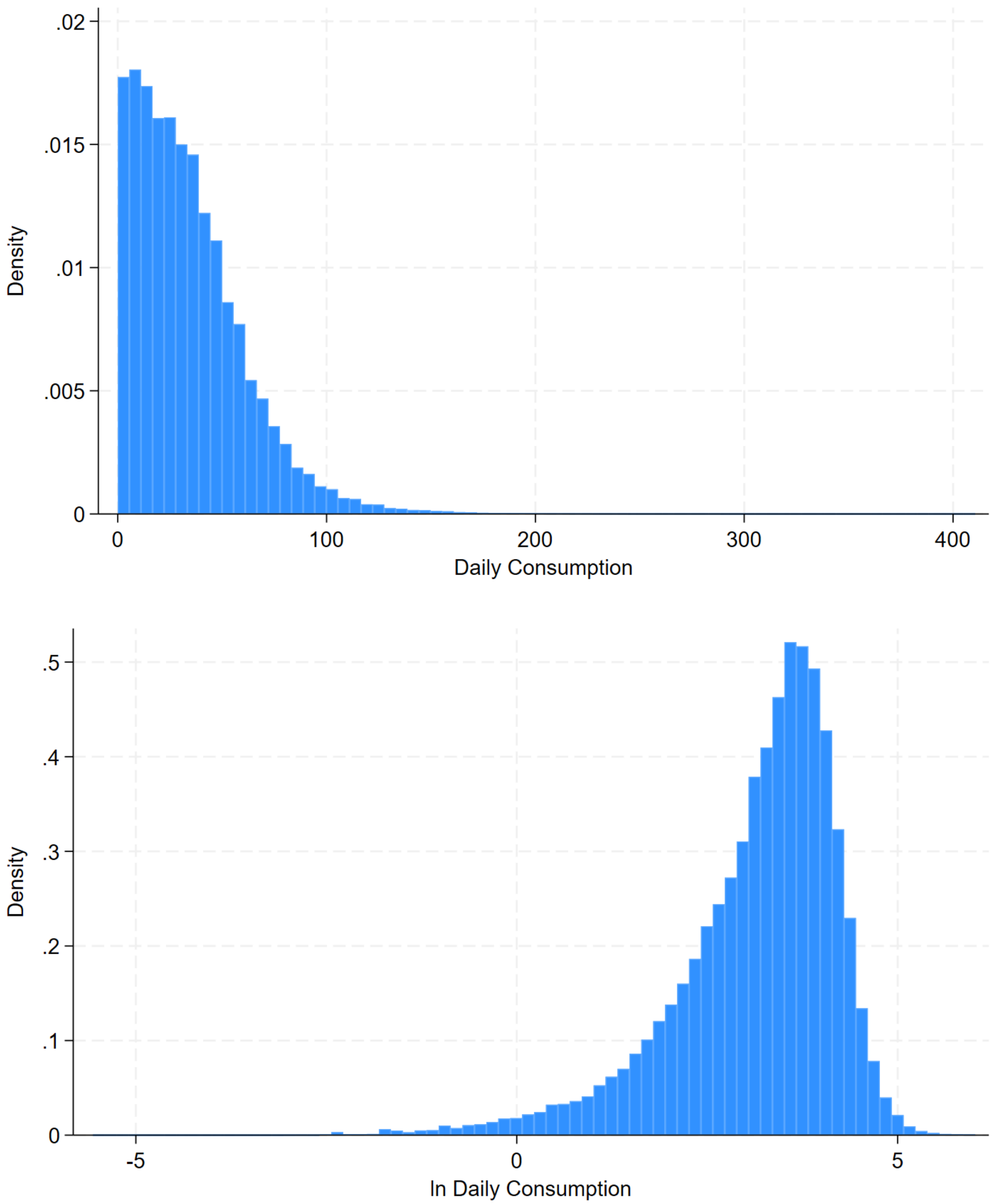
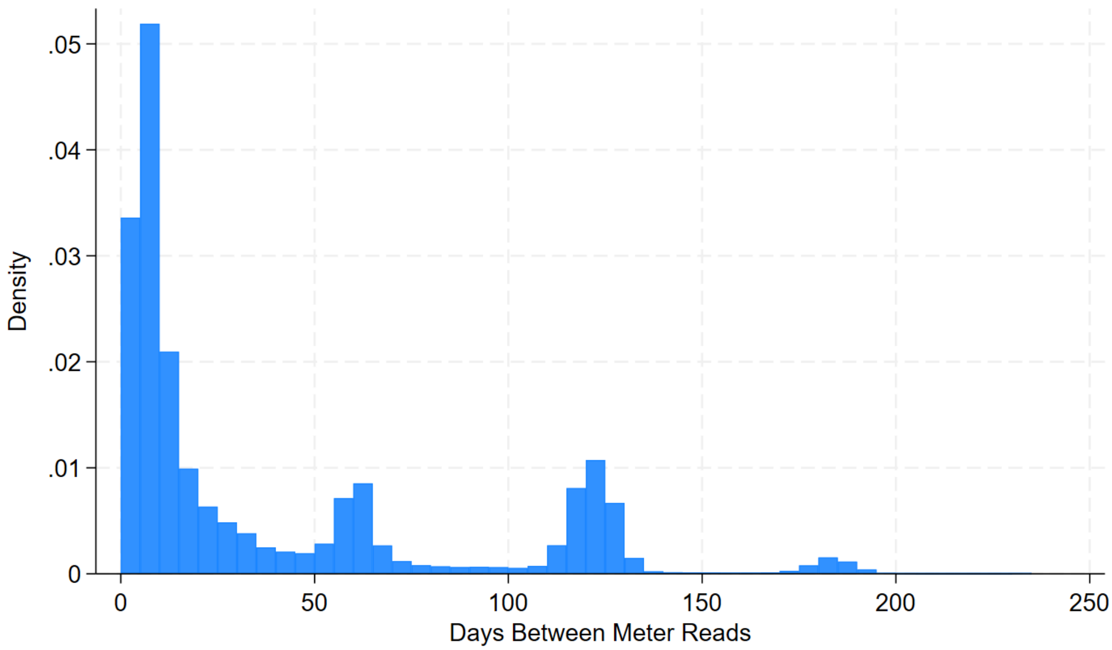


Figure 7: Distribution of Days Between Consumer Meter Readings(2018–2023)



where $\ln Q_{i,t}$ denotes the natural logarithm of *daily* gas consumption for household i during interval t; $\ln \bar{P}_{i,t}$ is the logarithm of the average retail price as defined in Section 3.2. Heating requirements are captured through $\ln HDD_{i,t}$, the logarithm of heating degree days within the interval. Household fixed effects α_i control for time-invariant heterogeneity, τ_t denotes quarterly time fixed effects and $\epsilon_{i,t}$ is the error term. The parameter η represents the price elasticity of demand, while γ captures the sensitivity of consumption to heating needs.

Our empirical strategy must account for the possible simultaneity of retail prices and quantity demanded. We account for this potential endogeneity by instrumenting for retail prices. An effective instrument must satisfy two criteria: the relevance condition and the exclusion restriction (Angrist & Pischke, 2009).

We choose the wholesale natural gas price as our instrument. Dutch day-ahead gas spot prices (TTFDA) were used to instrument for residential gas prices. As Section

3 has outlined, fluctuations in TTFDA prices are correlated with Irish retail prices. As wholesale gas is the primary component to the retail gas price, it is reasonable to assume that changes in wholesale prices drive changes in retail prices. This satisfies the relevance condition. As these prices are those of international commodity markets, it is reasonable to assume that wholesale price changes affect households through retail price changes alone, and not through any direct channel, such as through direct purchasing of natural gas on wholesale markets. Indeed, as our dataset comprises retail suppliers alone, this is excluded by definition.[5] As such, we are confident that this satisfies the exclusion restriction; these prices are correlated with the potentially endogenous explanatory variable of retail gas prices and affect consumption through this channel alone.

To incorporate this identification strategy into our empirical framework, we express the relationship between wholesale prices, retail tariffs, and household consumption using a standard two-stage least squares (2SLS) system. The first stage captures how variation in wholesale prices is transmitted into the retail tariff faced by households, while the second stage isolates the causal effect of retail prices on daily consumption using only the exogenous portion of price variation. The resulting specification is:

$$\begin{aligned} \text{First stage:} \quad & \ln \bar{P}_{it} = \pi_0 + \pi_1 W_t + \pi_2 \ln HDD_{it} + \tau_t + \alpha_i + u_{it}, \\ \text{Second stage:} \quad & \ln Q_{it} = \beta_0 + \eta \widehat{\ln \bar{P}}_{it} + \gamma \ln HDD_{it} + \tau_t + \alpha_i + \epsilon_{it}. \end{aligned} \tag{6}$$

[5]It may be the case that some households are familiar with developments on commodity markets or may be aware of current affairs developments which may inform them of future potential supply shortages. This may open up the possibility to some anticipatory effects, where consumers stockpile before a price increase is initiated, potentially biasing elasticity estimates downwards. While consumers can stockpile fuels such as gasoline and diesel, piped natural gas cannot be stockpiled, and consumption for heating and cooking must occur at the time of consumption. As such, we expect minimal bias due to anticipatory effects (Coglianese et al., 2017).

where W_t is the instrument and $\widehat{\ln P_{it}}$ is the predicted retail price from the first stage. The exclusion restriction is formalized by assuming that the error term ϵ_{it} is uncorrelated with the instrument, i.e. $\text{Cov}(\text{WholesalePrice}_t, \epsilon_{it}) = 0$.

We test the validity of our instrument by estimating a joint regression of consumption on both retail and wholesale prices (Table B.9). Retail prices exhibit the expected strong negative effect on demand. Wholesale prices, while statistically significant, enter with a positive coefficient, contrary to theoretical expectations, suggesting that this relationship is likely spurious. Importantly, the retail price coefficient is substantially larger in magnitude than the wholesale price coefficient, indicating that most variation in consumption operates through retail tariffs and supporting the plausibility of the exclusion restriction. Moreover, wholesale prices appear to be a strong instrument: we observe a Pearson/Spearman correlation coefficient of $\rho = 0.62$ between wholesale and retail prices, and the first-stage regression yields a highly significant F-statistic (shown in Table 6).

5 Results

This section presents estimates of the price elasticity of demand for natural gas for Irish residential consumers. We also test for heterogeneity in price responsiveness across observable dwelling characteristics.

5.1 Price elasticity of demand

Table 6 presents our primary price elasticity estimates. We report four specifications that incrementally introduce time-level fixed effects and the instrumental variables specification. All specifications include a household-level fixed effect.

The first-stage results embedded in Columns (2) and (4) provide strong support for our instrument. Wholesale gas prices are highly correlated with retail tariffs, with first-stage F-statistics well above conventional thresholds for instrument strength.

Column (1) provides a first benchmark where household-level fixed effects are controlled for alongside heating degree days. Both consumption and prices are in logarithmic form, and therefore a 1% increase in the independent variable is associated with approximately a β % change in the dependent variable. The estimated elasticity is –0.304, indicating that a 1% increase in prices is associated with a 0.30 % decrease in consumption. While not perfectly inelastic, this results suggests that Irish households are relatively inelastic to short-run variation in retail gas prices. This finding is consistent with the existing literature, which typically characterises residential energy demand as price inelastic in the short run due to limited scope for immediate adjustment in heating technologies, dwelling characteristics, and behavioural habits (e.g. (Alberini et al., 2020; Asche et al., 2008; Auffhammer & Rubin, 2018; Bianco et al., 2014; Erias & Iglesias, 2022)).

Column (2) reports results where the wholesale gas price is used as an instrument for the retail price. As with column (1), covariates are limited to household-level fixed effects and heating degree days. IV estimates yield a less elastic estimate of –0.192; a 1% increase in price is associated with a 0.192 % decrease in consumption. This is a price response of a lesser magnitude to the OLS estimates of column (1).

This is somewhat expected, the OLS regression specification of column (1) represents the relationship between consumption and retail prices, which may be biased by endogenous retail pricing and omitted demand/supply factors. The IV specification of column (2) instruments retail prices with wholesale prices. The estimate considers the consumption response via the component of retail price driven by wholesale-cost changes (i.e. wholesale cost pass through). Cost-induced retail price changes may operate through a tariff setting filter, a factor likely contributing towards a less elastic

IV estimate.

Column (3) considers the fixed effects estimates of column (1), with the addition of quarter-of-year fixed effects. Relative to the fixed effects specification of Column (1), Column (3) presents a slightly more elastic point estimate of –0.323. Controlling for time period fixed effects absorbs common seasonal demand shocks and season-specific price variation, as well as other unobserved time-varying factors that affect prices. A more negative coefficient suggests that such previously unobserved variation in price and seasonal demand is positively correlated. This result follows economic intuition, as prices increase with demand, which exhibits strong seasonal variation ((Auffhammer & Mansur, 2014; Erias & Iglesias, 2022; Rotondi, 2025)). As such, a more elastic coefficient is expected.

Finally, the regression specification of column (4) considers the instrumental variables specification of column (2) and also controls for quarter-of-year fixed effects as employed in Column (3). Household level fixed effects are also controlled for. Together, these adjustments address both time-invariant household heterogeneity, common temporal shocks and potential bias arising from simultaneity in the price-setting process. Column (4) presents a price elasticity estimate of –0.334, similar in magnitude to the effect of Column (2), albeit slightly more elastic.

This estimate falls in the mid-range of prior work, reflecting a moderate short-run responsiveness of household gas demand to retail price changes. For comparison, prior studies in European and North American contexts report short-run elasticities of gas demand ranging from approximately –0.1 to –0.5 (e.g., Auffhammer & Rubin, 2018; Bianco et al., 2014; Erias & Iglesias, 2022; Favero & Grossi, 2023). Our estimate is slightly more elastic than some country-level studies in Ireland and the UK, which typically find elasticities closer to –0.2.

The sign of the coefficient on the heating degree days is positive across all specifi-

Table 6: Baseline Specification

	Dependent Variable: ln(Avg Daily Consumption)			
	(1)	(2)	(3)	(4)
	FE	IV-FE	FE 2	IV-FE 2
ln(Marginal Gas Price)	–0.304***	–0.192***	–0.323***	–0.334***
	(0.00108)	(0.00160)	(0.000986)	(0.00153)
ln(Heating Degree Days)	0.309***	0.314***	0.0922***	0.0918***
	(0.000604)	(0.000602)	(0.000535)	(0.000532)
Q2			–0.590***	–0.590***
			(0.000652)	(0.000652)
Q3			–1.58***	–1.58***
			(0.00137)	(0.00137)
Q4			–0.438***	–0.437***
			(0.000635)	(0.000631)
Household FE	✓	✓	✓	✓
First stage: ln(Wholesale Price)		0.213***		0.211***
		(0.0000779)		(0.0000782)
First-stage F		3,783,553		1,673,181
Observations	27,576,674	27,576,674	27,576,674	27,576,674
Households	576,951	576,951	576,951	576,951
R^2	0.118	0.1061	0.394	0.3844

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes:
1 Retail gas prices are averaged monthly retail unit prices by supplier (2018–2023).
2 Household fixed effects control for all unobserved time-invariant characteristics of households. 3. Q1 is the base category for the time fixed effects in both FE 2 and IV-FE 2. Q1, Q2, Q3, and Q4 refer to calendar quarters. 4. Standard errors are clustered at the household level.

cations, indicating that a positive HDD value (reduction in daily mean temperature)[6] is associated with an increase in gas consumption. It is interesting to note that the heating degree day coefficient is reduced once we account for quarter-of-year fixed effects in columns (3) and (4). This is in line with expectations. Previous research has noted that weather patterns tend to be a significant predictor of natural gas consumption (Favero & Grossi, 2023; Zhu et al., 2018). Controlling for seasonal fixed effects therefore captures much of weather-related variation otherwise captured by heating degree days

Across all specifications, we control for the variation in the length of the consumption meter reading window. We do so by normalizing our dependant variable, consumption, by the number of days in the meter reading window to create an average daily consumption.

Q1 is the base category for the time fixed effects in both FE 2 and IV-FE 2. Q1, Q2, Q3, and Q4 refer to the first, second, third, and fourth quarters of the calendar year, respectively. Here, we can interpret the coefficients on the quarter time indicators as an average difference in consumption levels, relative to Q1. Again, the coefficients exhibit the expected signs. The coefficients imply that winter quarters (Q1 and Q4) see higher average consumption levels than summer quarters (Q2 and Q3).

Overall, our estimates suggest that the average short-run price elasticity of demand elasticity ranges between -0.192 and -0.334. These values are broadly in line with the existing literature.

[6]The interpretation of the heating degree day coefficient is somewhat counter-intuitive. As heating degree days is calculated as the difference between the daily mean temperature and a base temperature of 15.5 C, a positive HDD number indicates colder temperatures. Thus, the results suggest that a reduction in daily mean temperature is associated with an increase in gas consumption.

5.2 Heterogeneity by dwelling characteristics

In this section, we examine how the estimated price elasticities vary by dwelling type. Dwelling subgroups are identified through additional descriptive variables in the natural gas consumption dataset. To assess heterogeneity, we apply the same IV estimation strategy described in Equation 6 separately to each dwelling type d. For each subgroup we re-estimate both the first-stage and second-stage regressions within the relevant subsample. The fitted retail price, $\widehat{\ln \bar{\bar{P}}}^d_{it}$, is therefore obtained from a first-stage regression estimated on dwelling type d only. This feeds into our second-stage IV regression, Equation 7, separately for each dwelling type d.

$$\ln Q^d_{it} = \beta^d_0 + \eta^d \widehat{\ln \bar{\bar{P}}}^d_{it} + \gamma^d \ln HDD_{it} + \tau^d_t + \alpha^d_i + \epsilon^d_{it}, \tag{7}$$

This approach allows the elasticity parameter η^d to differ across dwelling types, while controlling for household fixed effects, time fixed effects, and heating degree days within each subgroup. Note that this specification controls for time-invariant household characteristics by construction, necessitating the separate subgroup analysis to reveal dwelling-specific heterogeneity. This estimation reveals significant variation in demand response by dwelling type.

Figure 8 suggests that detached homes demonstrate the most elastic demand response to changes in price.[7] Terraced and semi-detached homes appear to exhibit similar degrees of price elasticity to each other, and both show a less elastic demand response than detached homes. The subgroups with the most inelastic price response in the dataset are flats/apartments and bungalows. The variation in responsiveness between detached homes and other house types is in line with expectations. Alberini and Filippini (2011) note that larger homes tend to exhibit more elastic demand for

[7] In Figure 8, the error bars represent 95% confidence intervals.

energy. While we do not directly observe dwelling size, our house type categorisation may be considered a proxy; [8] on average, detached homes tend to be larger than semi-detached/terraced homes and flats/apartments. In addition, dwelling type may also proxy for higher average household income. Detached properties generally command a price premium relative to other types such as apartments and semi-detached houses in the Irish housing market (House Price.ie, 2025). More elastic average demand responses among detached homes may thus partly reflect an ability among wealthier households reduce their consumption. There are two potential mechanisms of action. First, a wealthier home may be better able to substitute away from gas as an energy source when faced with high prices (Alberini et al., 2011; Peersman & Wauters, 2024). It is also plausible that such households exhibit consumption above their subsistence level to a greater extent than households with lower incomes. Thus, they may have greater scope for demand reductions in the short-run (Alberini et al., 2011). The signs of the coefficients on the other covariates, i.e., ln(Heating Degree Days), the quarterly indicators (Q2–Q4), and the first-stage instrument ln(Wholesale Price), are consistent with our baseline results.[9]

In addition to examining the heterogeneity of the demand response by dwelling type, we consider demand response according to the number of bedrooms in the home. Household subgroups are identified based on the number of bedrooms recorded in the natural gas consumption dataset. To assess heterogeneity, we estimate our second-stage IV regression separately for each bedroom category, using the fitted retail price from the first-stage regression. This specification is similar to our baseline regression shown in Equation 6, with individual regressions run for dwellings where the number

[8]Fuerst et al. (2020) find that physical building characteristics, including dwelling type and size, are significant determinants of residential energy consumption, supporting the idea that heterogeneity in dwelling attributes may be associated with differences in price responsiveness.

[9]The full estimates for all household types are shown in Table B.1.

Table 7: Demand Response by Number of Bedrooms

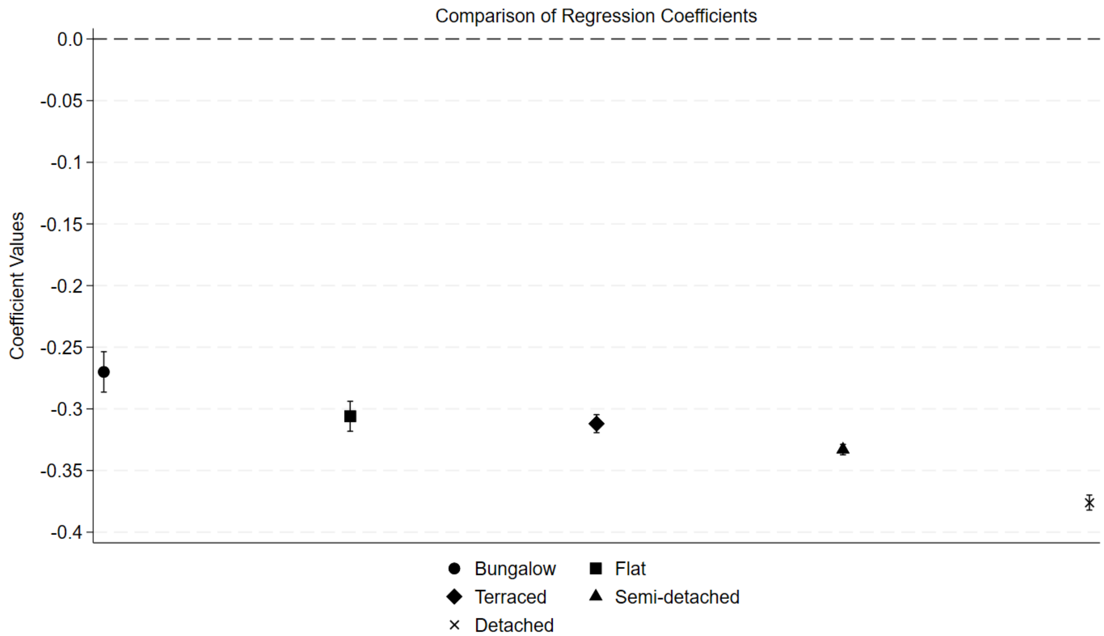
	Dependent Variable: ln(Avg Daily Consumption)	
	(1)	(2)
	Bedrooms ≤ 3	Bedrooms > 3
ln(Marginal Gas Price)	–0.316***	–0.407***
	(0.00484)	(0.0247)
ln(Heating Degree Days)	0.0629***	0.183***
	(0.00158)	(0.00936)
Q2	–0.586***	–0.507***
	(0.00198)	(0.0110)
Q3	–1.52***	–1.49***
	(0.00412)	(0.0308)
Q4	–0.420***	–0.521***
	(0.00173)	(0.0153)
Household FE	✓	✓
First stage: ln(Wholesale Price)	0.210***	0.213***
	(0.000246)	(0.00127)
First-stage F	463,238	98,857
Observations	23,475,759	4,100,916
Households	475,210	101,741
R^2	0.378	0.386

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Bedrooms ≤ 3 includes dwellings with one to three bedrooms; Bedrooms > 3 includes dwellings with four to six bedrooms. Q1 is the omitted quarter. Standard errors are clustered at the household level.

Figure 8: Coefficients from house-type subsample IV estimation



of bedrooms ranges from 1-3 and another for dwellings with more than 3 bedrooms. These results are presented in Table 7. Column (1) shows results for dwellings where the number of bedrooms ranges from 1-3, while Column (2) corresponds to larger dwellings with more than 3 bedrooms. The results reaffirm that larger dwellings exhibit more elastic demand responses and are consistent with Alberini and Filippini (2011), who find that larger homes tend to have more elastic energy demand. As discussed above , the likely mechanism for this is that larger dwellings have greater discretionary energy use, allowing households more scope to adjust consumption. Dwellings with more than 3 bedrooms also appear to respond to changes in weather to a greater extent than smaller, 1-3 bedroom homes. This is again consistent with the literature, where bigger homes tend to have a higher energy requirement, amplifying sensitivity to temperature fluctuations (Alberini et al., 2011; Peersman & Wauters, 2024).

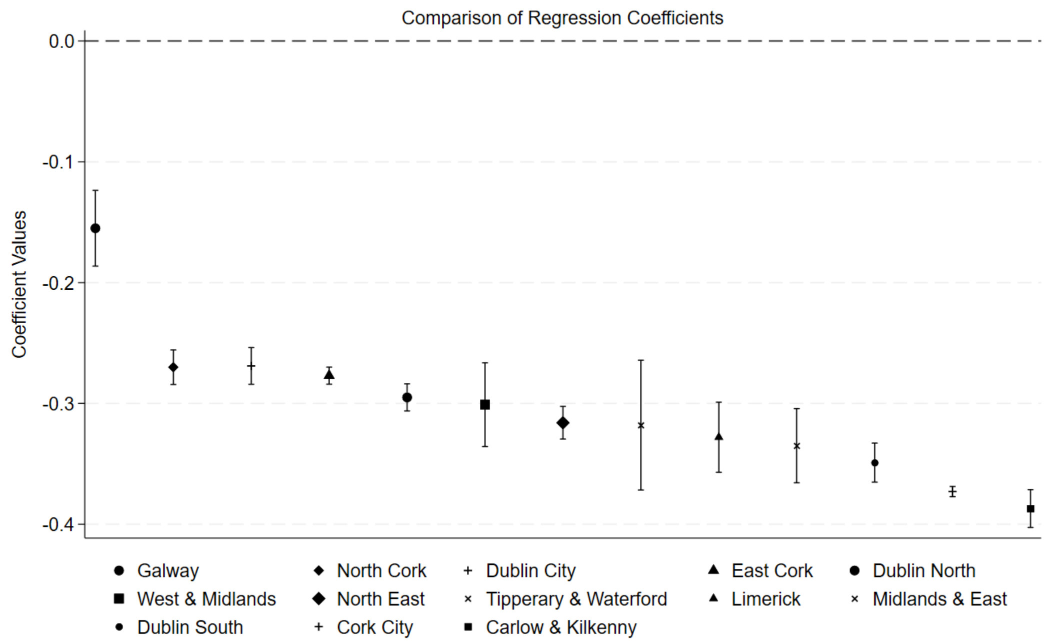


Figure 9: Coefficients from supply-area subsample IV estimation

We examine heterogeneity in demand responses by location to assess whether local supply conditions, regional infrastructure, or regional consumption norms affect price elasticities. Prior work shows that such spatial factors can influence residential energy demand and price responsiveness (e.g. (Alberini et al., 2011, 2020; Auffhammer & Rubin, 2018; Bianco et al., 2014; Erias & Iglesias, 2022; Favero & Grossi, 2023)), motivating our focus on regional variation. We estimate our preferred IV specification (Equation 6) separately for each gas supply area.

Figure 9 presents the resulting price elasticity estimates and 95% confidence intervals. Most estimates exhibit only modest variation. More urbanised areas, particularly Dublin City, Dublin North, and Dublin South, show relatively inelastic responses, with elasticities around -0.27 to -0.28, while several mixed urban–rural regions, such as Limerick, Cork City & West, and Carlow & Kilkenny, display somewhat more elastic demand, with coefficients closer to -0.35 to -0.40. Although confidence intervals overlap for many regions, pairwise differences between some urban and mixed regions are statistically different. The magnitude of this dispersion is roughly 0.10 to 0.12 elasticity points between the least and most responsive areas.

These patterns are broadly consistent with regional differences in dwelling characteristics, climate exposure, and heating intensity documented in the literature (Auffhammer & Rubin, 2018; Fuerst et al., 2020). Urban areas, characterised by smaller dwellings and potentially fewer short-run adjustment margins, may exhibit more inelastic demand, whereas mixed urban–rural areas with larger properties or greater heating reliance may display greater responsiveness. [10]

The presence of regional heterogeneity indicates that local structural characteristics contribute to variation in short-run price responsiveness. While wholesale price shocks are likely passed through uniformly in the retail market, households across supply areas do not respond identically. Instead, regional differences appear to reflect variation in housing stock and consumption norms. Two supply areas (Mayo and Tipperary South) yield imprecisely estimated coefficients, likely reflecting smaller sample sizes rather than genuinely atypical behavioural patterns, and are therefore excluded.

The final dimension of heterogeneity we examine concerns consumer's meter type. We estimate our preferred IV specification (Equation 6) separately for households with prepay and non-prepay meters. Table 8 presents the resulting estimates. Households with non-prepay meters exhibit somewhat higher price elasticity, -0.35, than prepay households , -0.32, though this difference is small. Responses to heating degree days

[10] The figure plots point estimates of the price elasticity of residential gas demand by gas supply area. Error bars represent 95% confidence intervals constructed from household-clustered standard errors. Gas supply areas correspond to geographically defined regions of the Irish gas distribution network, broadly reflecting urban, suburban, and mixed urban–rural areas. Supply areas Mayo and Tipperary South were excluded due to insignificant coefficients. Full regression results are reported in Table B.2.

also differ: non-prepay households increase consumption with higher heating demand, while prepay households show a slight reduction. Seasonal patterns further vary across meter types, with non-prepay households reducing usage in Q2–Q4 relative to Q1, whereas prepay households display the strongest reduction in Q3.

These differences may potentially reflect socioeconomic differences across households. A growing literature shows that prepay-meter households are not randomly distributed across the population but are disproportionately financially vulnerable. Fawcett et al. (2024) document that fuel poverty is highly concentrated among prepay-meter households. This evidence suggests that prepay-meter status could be associated with limited disposable income. If prepay households are more likely to be liquidity constrained or consuming closer to subsistence heating levels, they will likely exhibit slightly more inelastic patterns of demand (Alberini et al., 2011; Peersman & Wauters, 2024).

5.3 Robustness Checks

To assess the robustness of our estimated price elasticities to potential data quality issues, we re-estimate our preferred IV specification after each step of the data-cleaning process outlined in Section 3.1.1. Each cleaning step targets a specific source of bias. For example, removing households with non-positive or zero consumption addresses likely meter errors, billing anomalies, or non-residential usage that could generate spurious price responses. Excluding observations with extremely long billing intervals or daily consumption in the 99th percentile mitigates mechanical distortions from irregular readings or extreme outliers, which could otherwise cause bias in estimated elasticities. After applying these steps sequentially, we generate a series of 22 intermediate samples and trace a specification curve (Figure 10) showing how the estimated

Table 8: Demand Response by Meter Type

	Dependent Variable: ln(Avg Daily Consumption)	
	(1)	(2)
	Non-prepay	Prepay
ln(Marginal Gas Price)	–0.353***	–0.316***
	(0.00167)	(0.00321)
ln(Heating Degree Days)	0.156***	–0.097***
	(0.00059)	(0.00089)
Q2	–0.530***	–0.768***
	(0.00075)	(0.00108)
Q3	–1.525***	–1.757***
	(0.00147)	(0.00293)
Q4	–0.522***	–0.278***
	(0.00087)	(0.00073)
Household FE	✓	✓
First stage: ln(Wholesale Price)	0.220***	0.192***
	(0.00008)	(0.00014)
Observations	18,565,086	9,011,588
Households	523,955	52,996

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Prepay households are those that use meters that require payment in advance of consumption, while non-prepay households are billed retrospectively.Specification includes quarter time fixed effects where Q1 is the omitted quarter. Standard errors are clustered at the household level.

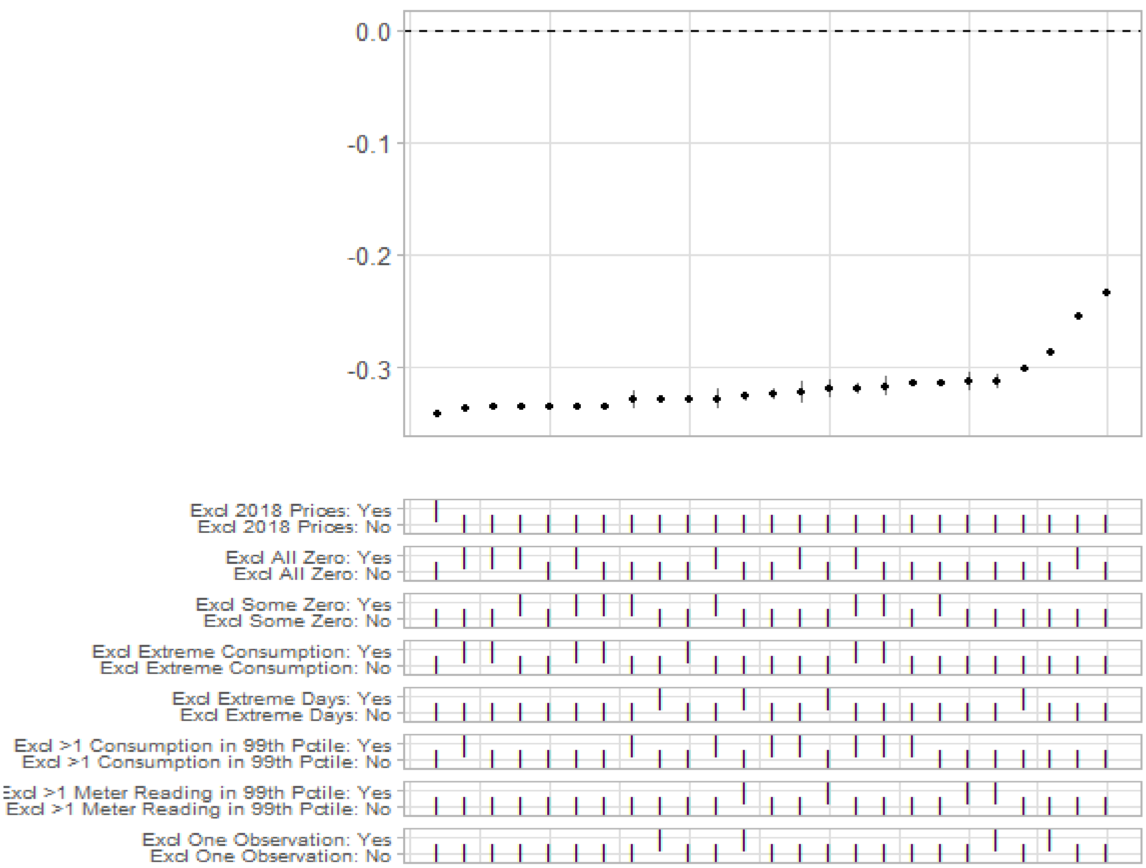
elasticity evolves with each change in data.

This procedure allows us to evaluate whether any single cleaning step drives the results. Across the sequence, the estimated price elasticity remains within a relatively narrow range of -0.31 to -0.34 in the majority of samples, despite substantial variation in sample size from nearly 31.6 million observations in the full dataset to 27.6 million in the final estimation sample. The clustering of estimates indicates that the IV results are not driven by any single data-quality issue.

However, in the most inclusive samples where extreme meter-reading intervals are retained, the elasticity shifts toward zero, with the full population sample yielding -0.234. This pattern is consistent with attenuation bias arising from measurement error in the consumption variable. Extreme meter-reading intervals increase noise in measured usage, as consumption is averaged over unusually long or irregular billing periods rather than rather than observed over the period in which households actually make consumption decisions. When such classical measurement error is present in the regressor, the estimated coefficient is biased toward zero (Ito, 2014; Reiss & White, 2005). Removing these extreme observations moves the elasticity in the expected direction (more negative), providing reassurance that our cleaning procedures are likely correcting this bias.

While the magnitude of changes in elasticity is modest, each cleaning step is theoretically justified and improves the reliability of the sample. The specification curve in Figure 10 demonstrates that our estimates are robust across data-cleaning decisions. Sample sizes and detailed cleaning steps are summarised in Table 2 and described further in Sections A.1 and A.2, with the full specification curve shown in Figure 10.

Figure 10: Specification curve for instrumental variable estimates under various sample data-cleaning restrictions



6 Discussion & Conclusion

This study analyses the price elasticity of demand for natural gas in Ireland. Our dataset details actual metered consumption for the entire population of residential consumers in Ireland and spans the six year period of 2018 to 2023. We use an instrumental variables approach to account for the potential simultaneity of prices and demand, and a rich set of individual and time fixed effects to account for unobserved household-level and seasonal heterogeneity.

We find that the price elasticity of demand is relatively inelastic in the short run, with coefficient values in the range of -0.192 to -0.334. This suggests that, on average, a one percent increase in prices leads to a 0.19 to 0.33 percentage point reduction in the residential demand for natural gas. While an inelastic demand response is somewhat expected, it remains an interesting finding. The period of analysis coincides with a period of extraordinary and salient growth in prices. Despite this, residential price elasticity of demand remained relatively inelastic.

The results of this analysis, suggesting an inelastic short run price elasticity, are congruent with other findings in the literature. Similar studies have found short run price elasticities in the region of -0.14 to -0.31 (Asche et al., 2008; Auffhammer & Rubin, 2018; Bianco et al., 2014; Erias & Iglesias, 2022; Zhu et al., 2018). Studies with results in this range tend to be sourced from a pan-European (Asche et al., 2008; Erias & Iglesias, 2022, e.g.) or US (Auffhammer & Rubin, 2018) context, where winter heating is a prominent consideration. Papers in a Mediterranean context, focusing on countries such as Italy (Favero & Grossi, 2023) and Greece (Kostakis et al., 2021) find more elastic results in the neighbourhood of -0.23 to -0.51 and -0.54 to -0.60, respectively. As noted by Erias and Iglesias (2022), there are between-country structural differences which may explain such differences. This paper sits with the former range.

There are a number of limitations to this analysis that must be taken into account. These are short run estimates and provide insight into the immediate response to changes in prices. Long-run estimates, where the capital stock is not fixed, will likely be more elastic. This should be the focus of further work, employing a longer time series. Indeed, the examination of the long-run adaption by households to a persistent elevation in gas prices would be of considerable interest. While providing direct insight into the welfare effects of price shocks, such as those related to the Russian invasion of Ukraine, indirect insight may be given to related policy decisions. In particular, analysing the price response to price shock that is expected to persist for the medium to long term can give meaningful empirical insight into the long-run behavioural response of natural gas consumers to policy interventions such as Pigouvian taxes.

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A Robustness Checks

A.1 Testing for bias due to zeros

Our gas variable undergoes a logarithmic transformation. This is primarily done for two reasons: it allows for proportional interpretation and it standardizes the sample towards a normal distribution.

Creating logarithmic transformations of our consumption values leads to missing values for observations where consumption equals 0. Due to 230,102 observations being 0 consumption periods, there is a potential for bias if these observations are removed during logarithmic transformation.

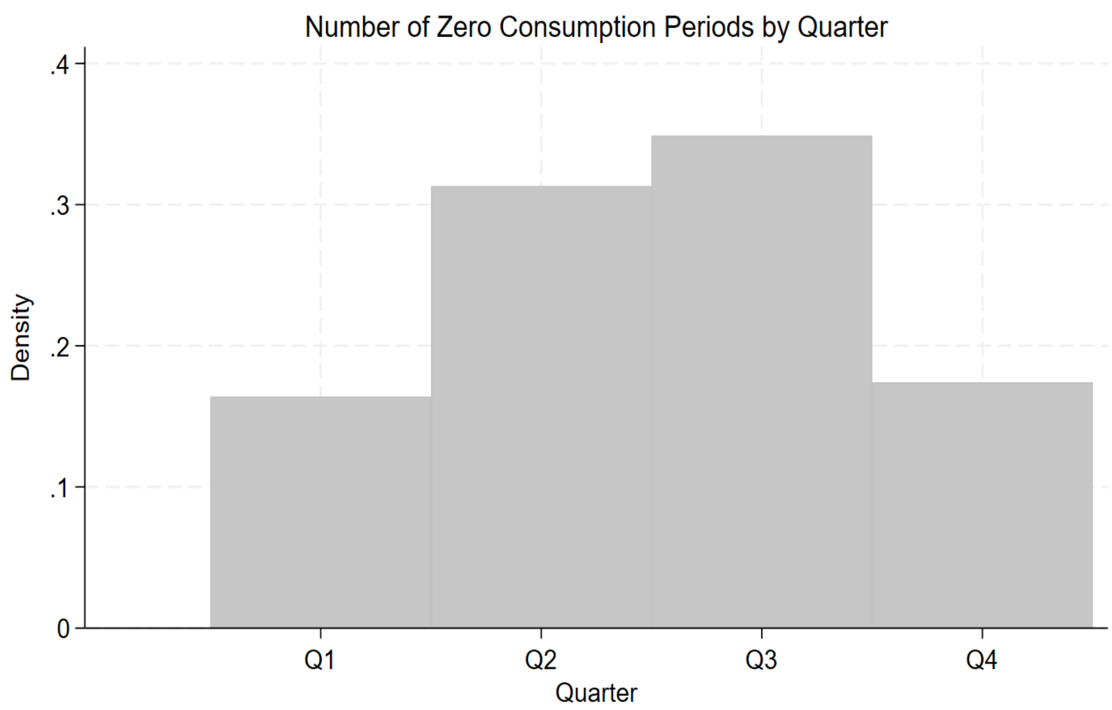

Figure A.1: Number of Zero Consumption Periods by Quarter

From Figure 2, which measures the variance of zero consumption periods across quarters from 2018-2023, we see a higher frequency of 0 observations in Q2 and Q3 than any other. This is likely driven by consumers who only use gas for residential heating purposes, not using the heating in periods of high temperatures. From this, we can assume that not accounting for this seasonal variation could potentially bias our estimates to some degree, even while accounting for weather effects across the seasons through heating degree days and quarterly time fixed effects.

To test, we run our model in absolute values and test on both the sample containing zero consumption observations and the sample where zero consumption observations are dropped. We test to ensure the magnitude of the association between price and gas consumption are in line with the primary specification, where zero-consumption observations are excluded. The results of this test are shown in Table B.5. By dividing the price coefficients by the mean daily consumption in each sample, we calculate implied price elasticities of -0.32 for the sample including zero consumption observations and -0.334 for the restricted sample (excluding zero consumption observations). From this, we conclude that the missing values generated through creating logarithmic transformations of our consumption variable do not significantly alter the estimates in our primary specification.

A.2 Testing for bias due to data cleaning

Our empirical strategy requires data cleaning to remove unusable or implausible observations from the raw consumption data. While each piece of data cleaning is motivated by clear data-quality concerns, it is important to assess whether these decisions introduce bias in our elasticity estimates. Table 2 summarises the effect of each piece of data cleaning on both the number of observations and the number of households retained in the analytical sample. Starting from an initial dataset of approximately 32 million readings for 710,866 households, the final estimation sample contains 27.6 million observations for 576,951 households. The removals are driven primarily by excluding households with extreme consumption values or implausibly long meter-reading intervals, each of which affects a substantive share of the data.

To evaluate the robustness of our results to data cleaning, we re-estimate our preferred IV specification with quarterly time fixed effects for every intermediate sample generated after each data-cleaning restriction. This sequence of estimates forms a specification curve, shown in Figure 10. Across the 22 alternative samples, the estimated price elasticity remains relatively stable. Point estimates range from approximately -0.34 to -0.31 for the large majority of specifications, with tighter standard errors for larger samples. Even when deliberately relaxing several key restrictions, such as retaining households with high consumption or highly irregular meter intervals, the elasticity never deviates far from the final baseline estimate of -0.334.

The only meaningful departures occur when the earliest and most inclusive samples are used (e.g., the full sample), where the elasticity moves toward zero in the range of -0.334 to -0.25. These differences are likely consistent with classical attenuation bias: data errors and mismeasured prices dampen the estimated behavioural response. Once these data issues are addressed, the elasticity stabilises.

B Additional results

Table B.1: Price Elasticity of Demand for Gas by Household Type

	Dependent Variable: ln(**Avg Daily Consumption**)				
	(1)	(2)	(3)	(4)	(5)
	Bungalow	Detached	Flat	Semi-Detached	Terraced
ln(Marginal Gas Price)	–0.270***	–0.376***	–0.306***	–0.333***	–0.312***
	(0.00835)	(0.00311)	(0.00621)	(0.00216)	(0.00372)
ln(Heating Degree Days)	0.0637***	0.120***	0.0501***	0.106***	0.0331***
	(0.00285)	(0.00111)	(0.00183)	(0.000758)	(0.00128)
Q2	–0.581***	–0.573***	–0.507***	–0.589***	–0.653***
	(0.00348)	(0.00139)	(0.00256)	(0.000913)	(0.00151)
Q3	–1.50***	–1.57***	–1.25***	–1.61***	–1.64***
	(0.00723)	(0.00288)	(0.00476)	(0.00191)	(0.00349)
Q4	–0.430***	–0.439***	–0.432***	–0.460***	–0.377***
	(0.00348)	(0.00137)	(0.00242)	(0.000927)	(0.00129)
Household FE	✓	✓	✓	✓	✓
First stage: ln(Wholesale Price)	0.210***	0.213***	0.210***	0.212***	0.210***
	(0.000437)	(0.000159)	(0.000302)	(0.000110)	(0.000194)
First-stage F	52,329	400,464	109,810	831,257	286,955
Observations	864,918	6,088,622	1,897,435	13,732,478	4,993,221
Households	18,628	135,077	45,749	303,456	74,041
R^2	0.378	0.386	0.379	0.387	0.382

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Q1 is the omitted quarter. Household fixed effects control for time-invariant household characteristics. Standard errors are clustered at the household level. All variables shown in logs are denoted with ln(·).

Table B.2: Price Elasticity of Demand for Gas by Supply Area

	Dependent Variable: ln(Avg Daily Consumption)														
	Carlow & Kilkenny	Cork City & West	Dublin City	Dublin North	Dublin South	East Cork	Galway	Galway & Mayo	Limerick	Midlands & East	North Cork & West	North East	Tipperary South	Tipperary & Waterford	West & Midlands
ln(MP)	-0.34***	-0.37***	-0.28***	-0.27***	-0.27***	-0.32***	-0.16***	-0.09**	-0.39***	-0.33***	-0.30***	-0.30***	-0.16	-0.35***	-0.32***
	(0.02)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.02)	(0.04)	(0.01)	(0.02)	(0.02)	(0.01)	(0.27)	(0.01)	(0.03)
ln(HDD)	0.08***	0.11***	0.09***	0.08***	0.04***	0.09***	0.11***	0.04**	0.11***	0.07***	0.15***	0.06***	-0.02	0.04***	0.08***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.18)	(0.00)	(0.01)
Q2	-0.61***	-0.60***	-0.53***	-0.59***	-0.64***	-0.60***	-0.34***	-0.38***	-0.63***	-0.57***	-0.53***	-0.62***	-0.54***	-0.63***	-0.43***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.02)	(0.00)	(0.01)	(0.01)	(0.00)	(0.09)	(0.00)	(0.01)
Q3	-1.62***	-1.63***	-1.36***	-1.58***	-1.66***	-1.59***	-1.32***	-1.38***	-1.75***	-1.54***	-1.49***	-1.50***	-2.13***	-1.82***	-1.58***
	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.02)	(0.01)	(0.21)	(0.01)	(0.02)
Q4	-0.45***	-0.44***	-0.45***	-0.44***	-0.37***	-0.42***	-0.49***	-0.44***	-0.46***	-0.50***	-0.40***	-0.41***	-0.66***	-0.44***	-0.60***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.02)	(0.00)	(0.01)	(0.01)	(0.00)	(0.21)	(0.00)	(0.02)
Household FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
First stage: ln(WP)	0.21***	0.21***	0.21***	0.21***	0.21***	0.21***	0.21***	0.21***	0.21***	0.21***	0.21***	0.21***	0.23***	0.21***	0.21***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)
R^2	0.38	0.38	0.39	0.38	0.38	0.39	0.38	0.38	0.39	0.38	0.38	0.38	0.39	0.38	0.38

Notes: Standard errors in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Standard errors clustered at the household level. All variables shown in logs are denoted with ln(·). MP = Marginal Price, HDD = Heating Degree Days, WP = Wholesale Price.

Table B.3: Specification with Average Prices Normalized by Consumption

	Dependent Variable: ln(Avg Daily Consumption)			
	(1)	(2)	(3)	(4)
	FE	IV-FE	FE 2	IV-FE 2
Average Price	–1.28***	–0.183***	–1.09***	–0.307***
	(0.000835)	(0.00146)	(0.000796)	(0.00129)
ln(Heating Degree Days)	0.160***	0.299***	0.0310***	0.0842***
	(0.000421)	(0.000591)	(0.000366)	(0.000478)
Q2			–0.464***	–0.557***
			(0.000507)	(0.000621)
Q3			–1.14***	–1.45***
			(0.000925)	(0.00129)
Q4			–0.288***	–0.418***
			(0.000446)	(0.000580)
Household FE	✓	✓	✓	✓
First stage: ln(Wholesale Price)		0.223***		0.230***
		(0.000142)		(0.000143)
First-stage F		1,569,276		711,644
Observations	27,576,674	27,576,674	27,576,674	27,576,674
Households	576,951	576,951	576,951	576,951
R^2	0.524	0.106	0.661	0.384

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Average price is normalized by total household consumption. Q1 is the omitted quarter. Household fixed effects control for time-invariant household characteristics. Standard errors are clustered at the household level. All other variables shown in logs are denoted with ln(·).

Table B.4: Specification with Average Prices Normalized by Meter Reading Length

	Dependent Variable: ln(Avg Daily Consumption)			
	(1)	(2)	(3)	(4)
	FE	IV-FE	FE 2	IV-FE 2
ln(Average Price)	–0.099***	–0.147***	–0.146***	–0.245***
	(0.001)	(0.001)	(0.001)	(0.001)
ln(Heating Degree Days)	0.320***	0.318***	0.099***	0.094***
	(0.001)	(0.001)	(0.001)	(0.001)
Q2			–0.589***	–0.585***
			(0.001)	(0.001)
Q3			–1.590***	–1.600***
			(0.001)	(0.001)
Q4			–0.481***	–0.490***
			(0.001)	(0.001)
Household FE	✓	✓	✓	✓
First stage: ln(Wholesale Price)		0.279***		0.288***
		(0.001)		(0.001)
First-stage F		121,483		87,347
Observations	27,576,674	27,576,674	27,576,674	27,576,674
Households	576,951	576,951	576,951	576,951
R^2	0.110	0.106	0.388	0.384

Notes: Standard errors in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Standard errors clustered at the household level. All variables shown in logs are denoted with $\ln(\cdot)$.

Table B.5: Baseline Specification in Absolute Terms

	Dependent Variable: Avg Daily Consumption	
	(1)	(2)
	With Zero Consumption	Without Zero Consumption
Marginal Retail Gas Price	–92.200***	–88.784***
	(2.531)	(0.219)
Heating Degree Days	0.011***	0.016***
	(0.000)	(0.000)
Constant	81.814***	51.921***
	(0.222)	(0.019)
Household FE	✓	✓
Time FE	✓	✓
Observations	28,586,739	27,576,674
R^2	0.291	0.384
Mean Dep. Var.	287.85	265.86

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The dependent variable is measured in absolute units of average daily gas consumption. Column (1) includes observations with zero recorded consumption; Column (2) excludes zero-consumption observations. Q1 is the omitted time period. Standard errors are clustered at the household level.

Table B.6: Baseline Specification Excluding 2018 Observations

	Dependent Variable: ln(Avg Daily Consumption)	
	(1)	(2)
	FE 2	IV-FE 2
ln(Marginal Gas Price)	–0.343***	–0.341***
	(0.000979)	(0.00155)
ln(Heating Degree Days)	0.0909***	0.0910***
	(0.000538)	(0.000537)
Q2	–0.599***	–0.599***
	(0.000663)	(0.000664)
Q3	–1.54***	–1.54***
	(0.00139)	(0.00139)
Q4	–0.430***	–0.430***
	(0.000669)	(0.000664)
Household FE	✓	✓
First stage: ln(Wholesale Price)		0.204***
		(0.0000765)
First-stage F		1,621,792
Observations	22,935,100	22,935,100
Households	576,219	576,219
R^2	0.389	0.367

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The sample excludes all observations from 2018. Q1 is the omitted quarter. Household fixed effects control for time-invariant household characteristics. Standard errors are clustered at the household level.

Table B.7: Elasticity Estimates with Different Price Sources

	Dependent Variable: ln(Avg Daily Consumption)		
	(1)	(2)	(3)
	Bonkers	CRU	Internet Archive
ln(Marginal Gas Price)	–0.335***	–0.286***	–0.245***
	(0.002)	(0.001)	(0.001)
ln(Heating Degree Days)	0.292***	0.104***	0.178***
	(0.001)	(0.001)	(0.001)
Q2	–0.617***	–0.599***	–0.640***
	(0.001)	(0.001)	(0.001)
Q3	–1.545***	–1.502***	–1.496***
	(0.001)	(0.001)	(0.002)
Q4	–0.442***	–0.429***	–0.239***
	(0.001)	(0.001)	(0.001)
Household FE	✓	✓	✓
First stage: ln(Wholesale Price)	0.201***	0.330***	0.159***
	(0.000)	(0.000)	(0.000)
First-stage F	3,578,147	3,149,117	678,037
Observations	14,439,249	19,946,294	8,212,356
Households	568,715	576,138	502,073
R^2	0.298	0.389	0.218

Notes: Standard errors in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Standard errors clustered at the household level. All variables shown in logs are denoted with $\ln(\cdot)$. Columns (1)–(3) use different retail price sources: Bonkers (2020–2023), CRU (2019), and Internet Archive (2018). Q1 is the omitted quarter. Household fixed effects control for time-invariant household characteristics.

Table B.8: Elasticity Estimates with Different Price Series Construction

	Dependent Variable: ln(Avg Daily Consumption)			
	(1)	(2)	(3)	(4)
	FE	IV-FE	FE 2	IV-FE 2
ln(Marginal Price)	–0.278***	–0.178***	–0.313***	–0.310***
	(0.001)	(0.001)	(0.001)	(0.001)
ln(Heating Degree Days)	0.291***	0.296***	0.086***	0.087***
	(0.001)	(0.001)	(0.001)	(0.001)
Q2			–0.603***	–0.603***
			(0.001)	(0.001)
Q3			–1.540***	–1.540***
			(0.001)	(0.001)
Q4			–0.444***	–0.444***
			(0.001)	(0.001)
Household FE	✓	✓	✓	✓
First stage: ln(Wholesale Price)		0.227***		0.227***
		(0.000)		(0.000)
First-stage F		5,597,394		2,337,500
Observations	27,576,674	27,576,674	27,576,674	27,576,674
Households	576,465	576,465	576,465	576,465
R^2	0.111	0.114	0.386	0.392

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Price series constructed using Bonkers data (2020–2023), CRU data (2019), and Internet Archive data (2018). Q1 is the omitted quarter. Household fixed effects control for time-invariant household characteristics. Standard errors are clustered at the household level. All variables shown in logs are denoted with ln(·).

Table B.9: Joint Estimation of Retail and Wholesale Gas Prices on Consumption

	Dependent Variable: ln(**Avg Daily Consumption**)
ln(Retail Gas Price)	–0.318***
	(0.001)
ln(Wholesale Gas Price)	–0.003***
	(0.000)
ln(Heating Degree Days)	0.092***
	(0.001)
Household FE	✓
Time FE	✓
Observations	27,576,674
Households	576,951

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This specification jointly includes retail and wholesale gas prices to assess their separate associations with daily consumption. Household fixed effects control for time-invariant household characteristics. Time fixed effects control for common shocks. Standard errors are clustered at the household level. All variables shown in logs are denoted with $\ln(\cdot)$.

C Regional summary statistics

Table C.1: Summary Statistics by Supply Area

Variable	Mean	SD	Min	Max
Carlow & Kilkenny				
Daily consumption	31.92	27.24	0.00055	410.12
Retail gas price	0.0813	0.0301	0.054	0.264
Standing charge	13.54	17.30	0	110.70
Wholesale gas price	0.0437	0.0416	0	0.327
Heating degree days	213.67	290.34	0.00	1971.96
Bedrooms	2.96	0.60	0	6
Meter reading frequency	142.59	124.15	1	924
Days between readings	39.18	47.72	0	234
Observations	285,829 (1.04%)			
Cork City & West				
Daily consumption	36.99	32.11	0.00052	410.58
Retail gas price	0.0806	0.0300	0.054	0.264
Standing charge	13.34	17.14	0	136.64
Wholesale gas price	0.0430	0.0418	0	0.572
Heating degree days	210.82	297.24	0	1948.66
Bedrooms	3.01	0.70	0	6
Meter reading frequency	158.11	133.30	1	1127
Days between readings	38.64	47.51	0	234
Observations	13,583,164 (49.25%)			
Dublin City				
Daily consumption	31.16	27.45	0.00055	410.41
Retail gas price	0.0816	0.0305	0.054	0.264
Standing charge	15.65	18.16	0	134.79
Wholesale gas price	0.0440	0.0428	0	0.572
Heating degree days	238.40	312.36	0	1907.24
Bedrooms	2.78	0.68	0	6
Meter reading frequency	132.76	121.18	1	934
Days between readings	45.11	50.09	0	234
Observations	4,648,613 (16.85%)			
Dublin North				

Variable	Mean	SD	Min	Max
Daily consumption	34.34	29.70	0.00057	410.37
Retail gas price	0.0811	0.0301	0.054	0.264
Standing charge	14.61	17.80	0	131.69
Wholesale gas price	0.0435	0.0424	0	0.443
Heating degree days	222.72	301.13	0	1892.24
Bedrooms	2.98	0.60	0	6
Meter reading frequency	136.95	118.36	1	785
Days between readings	42.15	49.38	0	234
Observations		1,138,389 (4.13%)		
Dublin South				
Daily consumption	34.87	26.94	0.00062	410.20
Retail gas price	0.0816	0.0302	0.054	0.264
Standing charge	11.63	15.98	0	120.94
Wholesale gas price	0.0439	0.0421	0	0.395
Heating degree days	184.03	278.89	0	1912.66
Bedrooms	2.95	0.61	0	6
Meter reading frequency	156.02	119.96	1	996
Days between readings	33.74	44.33	0	234
Observations		1,311,979 (4.76%)		
East Cork				
Daily consumption	34.49	28.05	0.00055	410.10
Retail gas price	0.0807	0.0299	0.054	0.264
Standing charge	11.92	16.30	0	125.12
Wholesale gas price	0.0432	0.0417	0	0.450
Heating degree days	160.30	245.90	0	1905.63
Bedrooms	3.01	0.54	0	6
Meter reading frequency	161.86	129.68	1	1183
Days between readings	34.57	45.13	0	234
Observations		1,534,409 (5.56%)		
Galway				
Daily consumption	27.45	23.01	0.00060	410.00
Retail gas price	0.0851	0.0334	0.054	0.198
Standing charge	20.59	19.62	0	110.22
Wholesale gas price	0.0456	0.0438	0.003	0.299
Heating degree days	328.05	373.79	0.00	1913.78

Variable	Mean	SD	Min	Max
Bedrooms	2.95	0.50	1	6
Meter reading frequency	96.26	110.92	1	544
Days between readings	59.88	55.37	0	234
Observations		190,487 (0.69%)		
Galway & Mayo				
Daily consumption	27.53	24.78	0.00061	410.05
Retail gas price	0.0847	0.0324	0.054	0.198
Standing charge	17.94	19.60	0	110.22
Wholesale gas price	0.0470	0.0445	0.003	0.299
Heating degree days	329.21	403.67	0.25	1930.29
Bedrooms	2.88	0.78	0	6
Meter reading frequency	136.69	142.07	1	608
Days between readings	50.92	53.89	0	232
Observations		42,957 (0.16%)		
Limerick				
Daily consumption	31.79	32.51	0.00055	410.07
Retail gas price	0.0807	0.0299	0.054	0.264
Standing charge	14.47	17.31	0	132.44
Wholesale gas price	0.0429	0.0409	0	0.381
Heating degree days	210.69	273.90	0	1786.78
Bedrooms	2.99	0.66	0	6
Meter reading frequency	126.24	111.58	1	713
Days between readings	41.95	47.59	0	234
Observations		1,162,379 (4.21%)		
Midlands & East				
Daily consumption	34.23	29.66	0.00055	410.08
Retail gas price	0.0828	0.0315	0.054	0.264
Standing charge	12.81	16.93	0	110.38
Wholesale gas price	0.0442	0.0426	0.003	0.304
Heating degree days	222.59	330.24	0.01	1999.29
Bedrooms	3.01	0.56	1	6
Meter reading frequency	160.71	134.31	1	769
Days between readings	37.37	47.30	0	234
Observations		344,373 (1.25%)		

Variable	Mean	SD	Min	Max
North Cork & West				
Daily consumption	29.51	25.19	0.00055	410.03
Retail gas price	0.0812	0.0303	0.054	0.264
Standing charge	16.18	18.42	0	112.13
Wholesale gas price	0.0434	0.0425	0.003	0.304
Heating degree days	229.81	295.08	0.00	1706.24
Bedrooms	2.99	0.70	0	6
Meter reading frequency	116.21	114.28	1	714
Days between readings	46.65	50.42	0	234
Observations		224,962 (0.82%)		
North East				
Daily consumption	32.55	26.46	0.00055	410.06
Retail gas price	0.0818	0.0305	0.054	0.264
Standing charge	11.91	16.11	0	120.47
Wholesale gas price	0.0444	0.0426	0	0.304
Heating degree days	200.67	295.80	0	2050.69
Bedrooms	2.92	0.61	0	6
Meter reading frequency	151.35	113.52	1	745
Days between readings	34.52	44.55	0	234
Observations		2,022,303 (7.33%)		
Tipperary South				
Daily consumption	32.96	35.95	0.010	410.00
Retail gas price	0.0804	0.0302	0.054	0.148
Standing charge	21.08	20.62	0.40	89.55
Wholesale gas price	0.0422	0.0395	0.006	0.202
Heating degree days	300.99	333.98	1.21	1505.85
Bedrooms	2.36	0.53	1	3
Meter reading frequency	72.52	53.17	1	125
Days between readings	57.71	55.69	1	224
Observations		238 (¡0.01%)		
Tipperary & Waterford				
Daily consumption	31.02	25.26	0.00055	410.04
Retail gas price	0.0806	0.0300	0.054	0.264
Standing charge	11.61	15.72	0	128.00
Wholesale gas price	0.0430	0.0414	0	0.412

Variable	Mean	SD	Min	Max
Heating degree days	172.65	258.17	0	1847.24
Bedrooms	3.01	0.59	0	6
Meter reading frequency	146.96	111.59	1	812
Days between readings	33.72	43.32	0	234
Observations		1,084,035 (3.93%)		
West & Midlands				
Daily consumption	29.81	27.99	0.00055	410.02
Retail gas price	0.0835	0.0328	0.054	0.264
Standing charge	18.19	19.30	0	124.86
Wholesale gas price	0.0447	0.0430	0.003	0.289
Heating degree days	303.75	380.15	0.03	1908.08
Bedrooms	2.91	0.60	0	6
Meter reading frequency	105.07	101.76	1	462
Days between readings	53.27	54.75	0	234
Observations		84,362 (0.31%)		

Notes: Daily consumption measured in kWh/day. Prices measured in €/kWh. Wholesale price is Dutch TTF day-ahead. Heating degree days (HDD) defined as $(15 - T_{mean})$ for $T_{mean} < 15°$C. Percentages in parentheses report each supply area's share of total observations ($N = 27{,}576{,}674$).