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Energy Economics

Analysis of individual natural gas consumption and price elasticity: evidence from billing data in Italy --Manuscript Draft--

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Abstract:	<p>The price elasticity of residential and non-residential energy demand is crucial for assessing energy policies and consumption forecasts.</p> <p>In this paper, using the monthly billing data of 51,177 end-users in Veneto (Italy), we implemented two panel-data models, analyzing the elasticity between natural gas demand and price variations. The models differ on how the possible endogeneity between price and demand is treated: (1) the total natural gas price is split into several components and we study only the natural gas price part free of endogeneity; (2) instrumental variable methods are used, considering two external instruments to regress the natural gas price from exogenous sources; (3) endogeneity is pictured by a dynamic panel model, correlating consumption with its first lag. We also investigated consumption patterns, underlining the influence of weather factors, market-liberalization, smart-metering technologies and macro-socioeconomic trends.</p> <p>The principal contribution of this paper is twofold: firstly, to supplement the slight empirical literature on natural gas consumption and price elasticity at the micro-level, based on the Italian market, providing a new contribution helpful in defining energy and environmental policies in Italy. Secondly, we provide an empirical method for utilities to exploit information that is often untapped such as billing invoices and technical data.</p> <p>The results show that residential end-users are more reactive to price changes than non-residents. However, the price elasticities found in this analysis are less than 1% for both groups, supporting outcomes found in other countries, i.e., natural gas consumers slightly react to price variations.</p>

Analysis of individual natural gas consumption and price elasticity: evidence from billing data in Italy

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October 6, 2022

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Abstract

The price elasticity of residential and non-residential energy demand is crucial for assessing energy policies and consumption forecasts. In this paper, using the monthly billing data of 51,177 end-users in Veneto (Italy), we implemented two panel-data models, analyzing the elasticity between natural gas demand and price variations. The models differ on how the possible endogeneity between price and demand is treated: (1) the total natural gas price is split into several components and we study only the natural gas price part free of endogeneity; (2) instrumental variable methods are used, considering two external instruments to regress the natural gas price from exogenous sources. We also investigated consumption patterns, underlining the influence of weather factors, market-liberalization, smart-metering technologies and macro-socioeconomic trends. The principal contribution of this paper is twofold: firstly, to supplement the slight empirical literature on natural gas consumption and price elasticity at the micro-level, based on the Italian market, providing a new contribution helpful in defining energy and environmental policies in Italy. Secondly, we provide an empirical method for utilities to exploit information that is often untapped such as billing invoices and technical data. The results show that residential end-users are more reactive to price changes than non-residents. However, the price elasticities found in this analysis are less than 1% for both groups, supporting outcomes found in other countries, i.e., natural gas consumers slightly react to price variations.

Keywords: Billing data, price elasticity, intra-day gas demand, panel data.

Research Highlights

- A new dataset based on microdata of monthly gas billings in the Veneto region (Italy) has been created
- Panel data models have been fitted to data to obtain price elasticities of gas consumption
- Weather data, latent factors, smart meter dummy and macro-trend variables have been included in the models
- Sources of endogeneity in the models have been treated using instrumental variables.
- Price elasticities for households and for non-households are consistent with previous results found in the literature

Credit author statement

The authors have shared all the steps of the work. Conceptualization, methodology, empirical analysis, and comments can be equally attributed to the authors. Filippo Favero wrote the R code.

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December 5, 2022

Abstract

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In this paper, using the monthly billing data of 51,177 end-users in Veneto (Italy), we implemented two panel-data models, analyzing the elasticity between natural gas demand and price variations. The models differ on how the possible endogeneity between price and demand is treated: (1) the total natural gas price is split into several components and we study only the natural gas price part free of endogeneity; (2) instrumental variable methods are used, considering two external instruments to regress the natural gas price from exogenous sources.

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The results show that residential end-users are more reactive to price changes than non-residents. However, the price elasticities found in this analysis are less than 1% for both groups, supporting outcomes found in other countries, i.e., natural gas consumers slightly react to price variations.

Keywords: Billing data, price elasticity, monthly natural gas demand, panel data.

22 1 Introduction

23 Natural gas at the local level is still the most important fossil fuel used for heating purposes by
24 households. Recent dramatic events related to the Ukrainian war, have raised awareness about
25 the heavy dependence of many European countries on the natural gas supply. Although the ulti-
26 mate decarbonization requires electric heating that is generated from non-fossil sources, it is quite
27 evident that, in the medium term, gas will be crucial along the path to decarbonization and envi-
28 ronmental protection¹. (Safari et al., 2019) argue that natural gas is a complementary transition
29 fuel towards a zero-carbon system based on renewable sources. They analyse the situation of four
30 countries, two with large gas reserves (Norway and Iran) e two importing gas (India and UK) trough
31 a STEEP analysis and conclude that, ignoring the role played by low emission fuels, the transition
32 to zero emission systems will lead to misleading policy action. However, the relevance of gas in the
33 green transition is controversial. Although natural gas might help the energy transition by reducing
34 emissions compared to coal, according to (Gürsan and de Gooyert, 2021), investments in new infras-
35 tructure to bring natural gas to households and firms could lead to long-term implications reducing
36 investments in renewable generation plants and green heating technologies, like heat pumps. This
37 can work against reaching climate goals.

38 Since 1996, the EU commission has taken measures concerning market access, regulation, con-
39 sumer protection, and support for interconnection to harmonize and liberalize the EU energy mar-
40 ket. These measures aim to foster competition (Opolska, 2017), creating a customer-oriented market
41 with low supply prices. creating a customer-oriented market with low supply prices. Since 2003, the
42 Italian energy market has been liberalized; private sellers can decide to operate in the market, and
43 users can freely decide which supplier to choose. However, the process is likely to terminate only at
44 the end of 2023, when the “Consumer-Protection Market” (hereafter CPM) ceases to exist. Each
45 consumer will have to switch to the “Free Market” (hereafter FM), in which the most convenient
46 supplier can be chosen.

47 In Italy, the retail energy market is regulated by the Italian Regulatory Authority for Energy,
48 Networks and Environment (ARERA). The principal elements of a typical natural gas bill are sales
49 costs, distribution costs, system expenses, and taxes. The market separation between CPM and
50 FM consumers influences only the selling component.

51 Italy’s natural gas price is subject to high volatility compared to other EU countries.² The
52 market transition from CPM to FM will bring further price variations and uncertainty for Italian
53 end-users. This process will affect utility revenues from customers. Therefore, energy operators
54 will need specific forecasting and analysis models to simulate market conditions after the tran-
55 sition from CPM to FM. Moreover, households, industries, and commercial activities may vary
56 their responses according to environmental ideology, expenditure, home characteristics, and energy
57 efficiency programs (Costa-Campi and Trujillo-Baute, 2015). For example, consumers may have dif-
58 ferent attitudes to the carbon-reduction efforts of authorities. Thus, environmental and economic
59 factors influencing energy use must be carefully defined to construct proper models of natural gas

¹<https://www.roadmap2050.eu/>

²ARERA Annual Reports, 2021, <https://www.arera.it/it/inglese/annual-report/relaz-annuale>.

60 consumption.

61 The principal purpose of this paper is to carry out a statistical case study from an original data-
62 set based on natural gas billing information for 51,177 final users in a province of Italy in the 2016-
63 2018 time interval. We analyze natural gas consumption patterns, considering several independent
64 variables: consumer characteristics, environmental and socioeconomic factors. In particular, we
65 carefully investigate the elasticity between natural gas prices and consumption both for FM and
66 CPM users. To carry out these analyses, we implemented static panel data models. Furthermore, a
67 dynamic panel model is preliminarily estimated (Appendix B) to investigate the possible influence
68 of past consumption patterns.

69 Unquestionably, the study of the correlation between demand and prices can have substantial
70 practical importance for utilities, regulators, and policymakers (Otero and Waddams Price, 2001).
71 This study can help energy suppliers in decision-making, contributing to the simulation of future
72 scenarios after the total liberalization of the Italian energy market.

73 We aim to contribute to the existing literature on natural gas demand in several ways. (1) To
74 the best of our knowledge, we implement the first gas consumption price-elasticity analysis using
75 disaggregated natural gas billing data for Italian consumers; (2) we propose three ways to treat the
76 endogeneity in the relationship between price and demand, a topic often ignored in the literature;
77 (3) the proposed models could easily be replicated in other countries or with different data-sets from
78 utilities that are a source of often untapped data; (4) we test the correlation of gas consumption
79 with various environmental factors (temperature, wind speed, air humidity, rainfall), creating a
80 reference base for subsequent studies; (5) this paper could be the first step in analyzing the effects
81 of smart-metering on consumer sensitivity to prices and consumption; (6) we test the ability to
82 use spatial and temporal macro trends to overcome the absence of individual information such as
83 income or home characteristics.

84 The paper is organized as follows. Section 2 discusses the existing literature on the estimation
85 of energy demand elasticities in Italy and elsewhere, internationally. Section 3 describes data
86 gathering, starting with the data for, and analysis of, environmental factors, billing and distribution
87 information, and macro trends. Furthermore, it illustrates the construction of the panel data models.
88 Section 4 shows and discuss the empirical results. The paper ends (section 5) with a discussion of
89 the policy, economic, and environmental implications.

90 2 Literature Review

91 Discussion of the relationship between energy consumption, consumer characteristics and price
92 variations has been intense in recent research. Energy consumption (e.g., electricity and natural
93 gas) has been investigated in several areas worldwide, at the state and regional level or according
94 to distribution, as well as at the individual customer level. However, unlike in the electricity sector
95 (e.g., Liddle and Huntington, 2021), the variability of natural gas consumption has not been analyzed
96 in detail. Therefore, an increasing amount of research focuses on the natural gas sector, which will
97 play a key role in future decarbonization scenarios, and seems to be more price-response variable
98 than electricity for homes (Trujillo-Baute et al., 2018; Woo et al., 2018).

99 This section reviews some studies of natural gas consumption to contextualize the empirical case
100 put forward in this paper. Furthermore, we cite some important findings for the electricity sector
101 that can be extended to natural gas. The two sectors are complementary and the two retail markets
102 in Italy have similar characteristics. However, in recent times, gas and electricity in Italy have
103 been partially seen as substitute goods because gas is increasingly being replaced by electricity for
104 heating purposes. This process has been certainly incentivized by recent policy measures subsidizing
105 the green transition in the building industry (Alberini et al., 2011). Several publications have
106 examined the Italian energy sector; however, few studies estimate price elasticities for natural gas
107 consumption, and even fewer use disaggregated data. For example, Besagni and Borgarello (2018)
108 analyzed energy consumption (electricity and heating) on the household scale, using survey data
109 obtained from the Italian National Institute of Statistics (ISTAT). The survey represents the Italian
110 population and focuses on household consumption and expenditure in 2015. They implemented a
111 regression analysis showing that, for electricity expenditure, socioeconomic factors such as income
112 and household structure are more significant than home and appliance characteristics. Conversely,
113 home variables are significant in studies of heating costs. Price elasticity has not been analyzed.

114 As observed by Bianco et al. (2014a,b), the investigation of energy demand in Italy is lacking
115 although it is fundamental for making informed policy decisions. They analyzed total Italian nat-
116 ural gas consumption, considering a multi-year time series regression both for the residential and
117 industrial sectors. For the residential sector, they considered aggregated data for natural gas con-
118 sumption at the national level, weather conditions, GDP, and natural gas prices. They developed
119 a demand equation that takes the form of a standard constant elasticity function of consumption
120 with the other variables. The elasticity values were studied, showing that natural gas consumption
121 is primarily influenced by climatic conditions and variations in GDP and is less sensitive to price
122 variations. This may be due to the high costs for users of implementing energy efficiency measures
123 or switching to other forms of energy for heating. The study calculated short-run price-elasticity
124 for the residential and industrial sectors, respectively, -0.15 and -0.34 .

125 Unlike the Italian case, several case studies with energy modeling and concerning price elasticity
126 exist in the international literature (Burke and Yang, 2016). Some countries have been studied
127 deeply, including Brazil (Pereira Uhr et al., 2019), China (Sun and Ouyang, 2016; Liu et al., 2018;
128 Zhang et al., 2018; Zeng et al., 2018; Dong et al., 2019), Greece (Kostakis et al., 2021), Japan
129 (Okajima and Okajima, 2013), Portugal (Silva et al., 2017), Switzerland (Boogen et al., 2017;
130 Filippini and Kumar, 2021), UK (Meier and Rehdanz, 2010) and USA (Fell et al., 2014; Miller and
131 Alberini, 2016).

132 As evidence of the recent growing interest, some meta-analyses have been completed in the last
133 few years. Labandeira et al. (2017) have recently carried out a meta-analysis in order to summarize
134 the principal empirical results in the literature on energy price elasticities. Their analysis shows that
135 price elasticities from panel data approaches are significantly higher than those from time series but
136 lower than cross-section models. The results for panel data show that, on average, the literature
137 has estimated price elasticity of natural gas demand between -0.2 and -0.5 .

138 Zhu et al. (2018) analyzed household electricity demand and identified the main factors affecting
139 residential energy elasticity. They presented a meta-analysis based on a comprehensive and sys-

140 thematic summary of 103 articles. The results show that price elasticity is sensitive to data types,
141 time intervals, and macro or microdata. Environmental characteristics can also affect short-term
142 price elasticity. Panel data have statistical significance, especially in short-term estimations, and
143 generate higher elasticities than other kinds of data. They found an average short-term electricity
144 price elasticity of -0.245 and -0.582 in the long term for panel data techniques.

145 Individual modeling is particularly relevant for local-level distribution. It provides more vari-
146 ability than top-down approaches, including inter-individual correlation information, useful to check
147 models and for criticism. Furthermore, once individual estimates are available, both top-down and
148 bottom-up approaches can be applied, forming various attractive aggregates, for instance, sums
149 across groups of customers, sums across time, or both (Brabec et al., 2008).

150 According to Fumo and Rafe Biswas (2015), the future of residential energy consumption fore-
151 casting is the analysis of individual homes, abandoning models that use data from surveys or describe
152 an entire population. This assumption is based mainly on the continuous deployment of smart me-
153 ters to end-users for natural gas and electricity (Batalla-Bejerano et al., 2016). However, as observed
154 by Ravnik and Hriberšek (2019), individual estimations require a sufficiently large consumer sample
155 size for acceptable results. Indeed, human behavior is a primary factor and can generate non-linear
156 variations in statistical consumption trends. This eventuality can be mitigated in large samples by
157 group behavior.

158 As observed by Halvorsen and Larsen (2013), price elasticity is influenced by the level of data
159 aggregation. The estimation of price elasticity from macro data, or aggregated microdata, is sig-
160 nificantly lower, in absolute terms, than from microdata. In some cases, elasticities for macro data
161 have also proved positive. Aggregation-level dependence is due to homogeneity assumptions about
162 consumer preferences and the distribution of prices in the sample. In light of this, we decided to
163 proceed with a panel data analysis, increasing the sample heterogeneity in prices and consumption,
164 improving the regression quality, and finding stable and coherent price elasticities.

165 Many recent empirical papers are relevant when panel data models are used to study energy con-
166 sumption. For example, Labandeira et al. (2012) studied electricity price elasticity at the individual
167 level in Spain, implementing a random effect panel model from monthly billing information. They
168 estimated residential and industrial electricity demand for 453,833 individuals from September 2005
169 to August 2007. They found a -0.2536 electricity demand elasticity for households and -0.0308
170 for industrial activities.

171 Miller and Alberini (2016) studied the aggregation effect on a panel data model with a different
172 data-set at the individual level. The household data-set showed that using more aggregated obser-
173 vations produces a more inelastic demand. However, aggregating the utility level data to the state
174 level makes the demand more elastic.

175 In another paper, Alberini and Filippini (2011) analyzed residential electricity demand using
176 annual aggregated data at the state level. They implemented static and dynamic data panel models
177 for 48 US states from 1995 to 2007, finding a range of short-run elasticity from -0.08 to -0.15 .
178 This is relatively small, compared to the result of Alberini et al. (2011), who analyzed microdata at
179 the household level for the 50 largest metropolitan areas in the US in the period 1997-2007. They
180 regressed energy consumption from environmental and household characteristics as well as price

181 data. From a static model, they estimated own-price elasticity of electricity demand in the -0.860
182 to -0.667 range, while the own-price elasticity of gas demand is in the -0.693 to -0.566 range.

183 (McIntyre, 2018) questions the assumption usually made in the literature that the relevant price
184 for estimating the elasticity of energy demand is the contemporaneous price. Using microdata from
185 the UK Living Cost and Food survey in 2007-2014, he finds that estimated price elasticities of gas
186 demand decrease when lagged prices are included in the model.

187 Another essential issue raised by demand-price analysis is the possible source of endogeneity.
188 As reported by Auffhammer and Rubin (2018), the endogeneity from classical market equilibrium
189 theory can generate simultaneity. Another endogeneity source is typical of retail energy markets,
190 where the price is a demand function in a block tariff scheme. The authors tried to resolve the first
191 kind of endogeneity using natural gas spot prices as instruments. For the second source, they used
192 spot prices and baseline prices to construct a simulated instrument. They found that the natural gas
193 average price elasticity of demand for households ranges from -0.17 to -0.23 . Furthermore, they
194 observed that individuals with low and high incomes are both price inelastic during the summer.
195 During the winter, low-income households are more price-sensitive. The endogeneity issue has been
196 also raised by (Alberini et al., 2020) who estimate the price elasticity of natural gas demand in a city
197 of Ukraine. Using billing data information collection by an ad-hoc survey the authors estimate the
198 elasticity of gas demand to prices by a panel regression. The source of endogeneity is related to the
199 block pricing system applied in Ukraine as the consumer selects both its consumption level and the
200 corresponding tariff. The endogeneity issue is addressed by a two stage least square estimation where
201 the instruments used in the first stage are allowance and discount off the regular tariff obtained by
202 a group of households.

203 The research on price elasticity might have practical policy implications. For example, Xiang
204 and Lawley (2019) estimate the effects of the 2008 carbon tax in the British Columbia on residential
205 natural gas consumption per capita. Implementing a panel data analysis, they used several input
206 variables with data from 1990 to 2014, such as gas demand, weather conditions, prices, building
207 and population characteristics. Their results are consistent with the supposition that the residential
208 demand is price and tax inelastic. Indeed, factors such as weather and household characteristics
209 are essential in the short and medium-term, compared to gas and household incomes. However,
210 they were able to assess the long-term impacts of a carbon tax. The overall results suggest that a
211 carbon tax of 1 cent/m³ reduces per capita natural gas consumption by 3%. Hence, the result can
212 be interpreted as negative price-demand elasticity. A recent study by (Liu et al., 2022) has found
213 that a carbon tax to stimulate the use of “clean” fuels in China, using macro-panel data in the time
214 span 2005-2019 has implied an increasing substitution of natural gas for coal and LPG over time;
215 on the other hand electricity has gradually replaced the use of natural gas.

216 Although not focused on price elasticity, an important contribution is given by (Auffhammer,
217 2022) who estimates the effect of climate change in California on electricity and gas consumption.
218 Using a massive micro-dataset containing information from gas and electricity bills paid by house-
219 holds, the author finds that the increased demand for cooling systems due to high temperature
220 will induce a higher demand for electricity, but projections show that this increased electricity
221 consumption will be more than offset by savings in directly consumed natural gas.

222 Some of the principal results from natural gas consumption analysis and price elasticity are
 223 summarized in Table 1.

224 3 Data and Methodology

225 We collected monthly natural gas distribution information from about 1,800,000 monthly bills from
 226 the Vicenza and Treviso districts in the Veneto region of Italy. Agsm Aim Energia Srl and V-Reti
 227 Spa - respectively the principal energy provider and local energy distributor in the area - provided
 228 the data-sets.

229 The population of the area is about 250,000, and the total number of natural gas end-users was
 230 approximately 140,000 on December 31, 2018. The balanced sample size analyzed in this paper
 231 is about 51,177 consumers, considering only consumers with constant combination of User-Home-
 232 Seller.

233 The monthly data variation is from January 1, 2016 to December 31, 2018 (36 time frames). To the
 234 billing and distribution information, we added environmental factors collected from seven weather
 235 stations, and macro socio-economic trends from Italian institutional websites.

236 Two kinds of consumers can be identified in the data-set: “Households” and “Non-households”. The
 237 household cluster includes end-users that consume natural gas for residential and private use (e.g.,
 238 heating systems, cooking, cooling, etc.). The non-household cluster includes commercial consumers
 239 (e.g., industry, shops, restaurants, artisans, service activities, etc.).

240 The variables used in this paper and a summary of statistics are set out in tables 2 and 3. A detailed
 241 description follows in the next subsection.

242 3.1 Data Collection

243 Billing data

244 Natural gas consumption (Q) is the quantity in Sm^3 (standard cubic meters) of gas consumed
 245 monthly by each end-user. We implement the panel data models utilizing logarithmic natural gas
 246 consumption as the dependent variable to directly study gas price elasticity (1% variation in natural
 247 gas prices would lead to a percentage variation in natural gas consumption). Moreover, it is helpful
 248 to mitigate the effects of outliers and standardize the sample toward a normal distribution.

249 Individual prices are directly derived from the billing data-set. The data are heterogeneous for
 250 individuals (households, industrial, and commercial activities) and market conditions (CPM and
 251 FM). Moreover, end-users joined the FM at different times with different tariff structures. For
 252 price-demand elasticity the total price (*price.tot*) faced by each individual is the relevant datum -
 253 i.e., the sum of the selling price (*price.sel*) and distribution price (*price.dis*) -.

254 The distribution price is divided into several brackets in a block tariff system. The allocated con-
 255 sumption in each group is consecutive, starting at the beginning of the calendar year, so consumption
 256 in the first months of the year is in the first group, in later months in subsequent groups and so on.
 257 Figure 1 shows box-plots describing variations in the price components over time. The sample is
 258 divided into CPM (1.a and 1.c) and FM consumers (1.b and 1.d).

Author(s)	Data	Technique	Price elasticity
Natural Gas consumption			
Meier and Rehdanz (2010)	Residential energy consumption data in UK Survey 1991-2005 5,000 households	Random effect panel data	-0.34 to -0.56
Alberini et al. (2011)	US household-level energy consumption Survey 1997-2007 98,772 observations in 54 cities	Static and dynamic panel model Variables: energy prices and home characteristics	$\simeq -0.7$ (short-run) $\simeq -0.5$ (long-run)
Auffhammer and Rubin (2018)	Residential natural gas data in California Billing data 2003-2014 2,526,503 households	Instrumental panel data with different instruments	-0.23 to -0.17
McIntyre (2018)	Residential natural gas and electricity data in UK UK Living Cost and Food survey 2007-2014	Quadratic Almost Ideal Demand System (QUAIDS) model	-0.66 to -0.51
Zhang et al. (2018)	Short and long run price elasticities of gas consumption in China for various sectors China Energy Statistics Yearbook 1992 - 2015 Sectoral macro data on gas consumption	Gas demand function estimated by the ARDL approach	Short and long run price elasticities of residential sector: -0.233 (same value)
Zeng et al. (2018)	Chinese residential energy consumption Survey 2014 Cross-sectional 1,035 observations	Logarithmic OLS, IV	-0.898 to -0.965
Dong et al. (2019)	Price elasticities of gas consumption in 30 Chinese provinces China Energy Statistical Yearbook 1999 - 2015 Unbalanced macro panel dataset	Panel common correlated effects mean group estimator	0.02 to 0.04
Alberini et al. (2020)	Residential natural gas data in the city of Uzhhorod (Ukraine) Billing data and Survey data 2013-2017 500 households	Instrumental panel data with instruments	-0.22 to -0.07
Filippini and Kumar (2021)	Residential natural gas consumption in Switzerland Household level data 2010 - 2014 Unbalanced panel of 958 households	Fixed Effect model and Random Effect model with Mundlak's adjustment	$\simeq -0.73$
Kostakis et al. (2021)	Residential gas consumption in Greece Household level panel data 2012 - 2019 185 cohorts of household's heads	Static and dynamic panel models	-0.65 to -0.54
Auffhammer (2022)	Residential natural gas data in California Billing data 2004-2015 More than 90 millions bills	Two-stage log-linear regression models estimated locally	-

Table 1: Principal results for energy price elasticity and gas demand variation from micro- and macro-data.

Description	Source	Variable	Unit
Dependent variable			
Natural gas consumption	Billing data	Q	[Sm^3]
Price			
Natural gas price (total)	Billing data	$price.tot$	[€/ Sm^3]
Weather variations			
Heat Degree Days	ARPAV	hdd	[°C]
Humidity average	ARPAV	hum	[%]
Rain precipitation	ARPAV	$rain$	[mm]
Wind velocity average	ARPAV	$wind$	[m/s]
End-user characteristics			
Presence of a smart-meter	Distribution data	$smart.meter$	dummy
Consumption self reading by end-user	Distribution data	$self.read$	dummy
Number of PODs in the same building	Distribution data	$n.dwell$	set of dummies
Social welfare aid program participation	Billing data	$welf.aid$	[dummy]
Free-market end-user	Billing data	$free.market$	dummy
Socio-economic trends			
Average size of home	ISTAT	$av.s.dwell$	[m^2]
Building-age index	ISTAT	$build.age.index$	[-]
Gross average income	Italian ministry of finance	$gross.income$	[€ · 10^{-3}]
Population dependence index	ISTAT	$dep.index$	[-]
Time fixed effect			
Quarter	–	$q1, q2, q3, q4$	dummy

Table 2: Variables used in panel data models for the individual i and month t .

	Households					Non-households				
	mean	max	min	St. Dev.	St. Dev./mean	mean	max	min	St. Dev.	St. Dev./mean
Q	89.95	997.45	2	96.5	1.07	400.24	67,793	2	1620.69	4.05
$\ln(Q)$	3.91	6.91	0.69	1.18	0.3	4.45	11.12	0.69	1.6	0.36
$price.sel$	0.26	0.38	0.18	0.03	0.12	0.29	0.38	0.17	0.04	0.14
$price.dis$	0.13	0.17	0.05	0.03	0.23	0.13	0.17	0.04	0.03	0.23
$price.tot$	0.39	0.55	0.25	0.04	0.1	0.42	0.56	0.24	0.05	0.12
hdd	180.79	567	0	178.72	0.99	180.59	566.8	0	178.42	0.99
$wind$	0.86	1.8	0.3	0.31	0.36	0.86	1.8	0.3	0.31	0.36
$rain$	83.26	271	0	53.9	0.65	83.85	271	0	53.91	0.64
hum	23.81	51	6	7.24	0.3	23.77	51	6	7.2	0.3

Table 3: Summary statistics for households and non-households.

259 The cross-section variation of $price.sel$ is almost negligible for CPM consumers. The small variation
260 is due to the sample spatial variability that slightly influences the price for different local adminis-
261 trations. Conversely, the $price.sel$ for FM users derives from a direct agreement between the seller
262 and consumers, with greater variability. In both cases, the quarterly structure of the sales tariff is
263 clear, i.e., the price remains the same for three-month periods. In figure 1.b, the mean of the selling
264 prices is slightly different for CPM and FM groups. FM sellers typically encourage consumers to
265 switch with affordable prices, similar or equal to CPM.

266 The $price.dis$ component does not depend on the consumer choice, either CPM or FM. Figures 1.c
267 and 1.d show how the block tariff system for the distribution prices works. There is a correlation
268 between distribution prices and cumulative natural gas consumption during the year. In January

269 (months 1, 13, 25 in the sample), the *price.dis* is conspicuously lower. End-users are typically in
 270 the first consumption step. At the end of the year (October-December), the price flattens around a
 271 steady-state value reached by almost all users, corresponding to a quantity of gas in the range from
 272 1000 to 2000 $Sm^3/year$.³

273 The free-market variable (*free.market*) is a dummy variable indicating the market character-
 274 ization of each end-users. The value of consumers in the free-market increased over the months,
 275 especially for the household group, reaching the 40% at the end of 2018. The non-household group
 276 is almost static over time and was in the free-market since before the period under analysis. In
 277 January 2022, all Italian energy consumers will be in the free market.

278 The social welfare variable (*welf.aid*) is considered as a low-income index constant over time.
 279 Indeed, the balanced data-set is constructed for static end-users; hence, it is reasonable to consider
 280 access to social welfare subsidies as a threshold for low-income end-users during the entire period
 281 under analysis. Of the 49,156 residential consumers in the sample, 2,165 end-users received a social
 282 welfare subsidy for energy consumption.

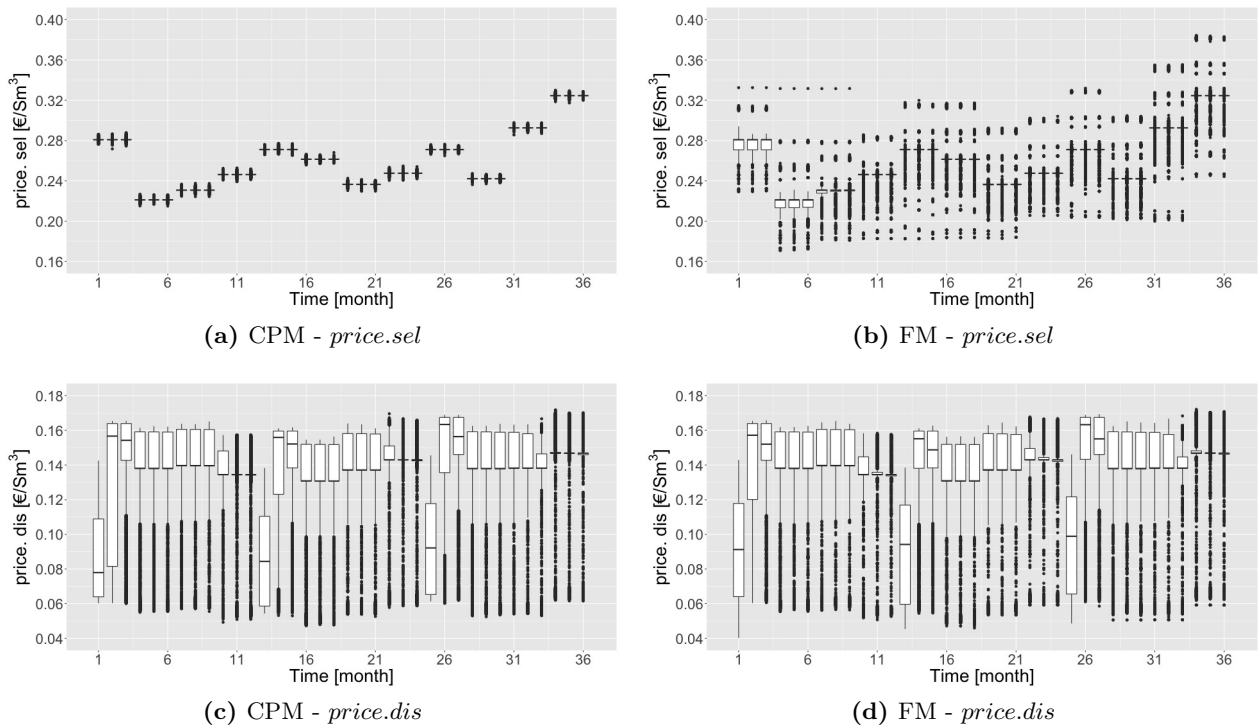


Figure 1: Box-plots of the price variation over time for CPM and FM users.

Weather data

283
 284 The territories analyzed in this paper are located in the Po Valley. The climate is continental
 285 with cold and humid winters and hot, muggy summers. The hills and mountains surrounding the
 286 area create a natural barrier to rain and storms.

287 The environmental data-set was collected from the ARPAV (Provincial Agency for Environmental

³ARERA natural gas prices. <https://www.arera.it/it/prezzi.htm>.

288 Prevention and Protection in Veneto).⁴

289 Generally, in energy demand analysis, the most significant environmental variable is temperature
 290 (Swan and Ugursal, 2009). This is true especially in the natural gas sector since it is mainly used for
 291 residential, commercial, and industrial heating. Gas consumption comprises two parts: one small
 292 and unrelated to temperature (e.g., cooking, hot water, industrial production) and another, larger,
 293 related to the outside temperature (e.g., heating purposes).

294 The variable used to describe temperature variations is the “heating degree days” (*hdd*), calculated
 295 as the difference between the daily mean temperature and a base temperature of 18°C (see equation
 296 1).

$$hdd = \begin{cases} \sum_{d=1}^{31} (18 - T_d) & \text{if } T_d < 18 \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

297 The temperature is not the only environmental variable with a possible key role; we also collected
 298 the monthly mean of humidity (*hum*), wind speed (*wind*), and the quantity of rainfall (*rain*).
 299 As shown in previous studies (Soldo, 2012) (Valor et al., 2001), *hdd* is the main driver of energy
 300 consumption; however other meteorological variables may improve estimation results when energy
 301 consumption is analyzed.

302 Distribution data

303 The billing data were interpolated with the distribution information provided by the local distrib-
 304 utor. The distribution data include: consumer spatial location (address and local administration),
 305 presence of smart meters, self-meter reading by end-users, and manufacturing, which is significant
 306 for non-household consumers.

307 The local administration is identified to assign the relevant weather station and the specific macro
 308 trends to each end-user. Furthermore, the address is helpful in constructing the *n.dwell* variable,
 309 representing the number of homes in the same building. The *n.dwell* variable is constructed using
 310 the spatial indication of addresses, street numbers, and ZIP codes.

311 The correlation between the *n.dwell* and gas consumption is supposed to be negative for two
 312 reasons. First of all, because single homes usually have more surface area to heat. Secondly, several
 313 homes in the same building contribute to overall heating, decreasing heat loss.

314 The presence of smart meters is indicated with a dummy variable (*smart.meter*). Energy
 315 smart-meters will become essential in the future, due to the development of smart city technolo-
 316 gies ((Batalla-Bejerano et al., 2020)). These innovative devices enable two-way communications
 317 with real-time control of different variables (flow, volume, temperature, pressure), recorded every
 318 15 minutes. In Italy, ARERA has required natural gas providers to replace at least 85% of tra-
 319 ditional meters with smart ones by 2023. Therefore, Italian utilities have run several replacement
 320 campaigns. For example, since 2016, the local distributor of the analyzed area has started a re-
 321 placement campaign aiming to dismiss most of traditional meters. Therefore, this technology is not
 322 uniquely reserved to new buildings, but is accessible to all users. As shown in figure 2, the number

⁴Regional Agency for Environmental Prevention and Protection of Veneto, <https://meteo.arpa.veneto.it>. Last accessed: May 2022.

323 of end-users with smart metering has sharply increased over 2016-2018.

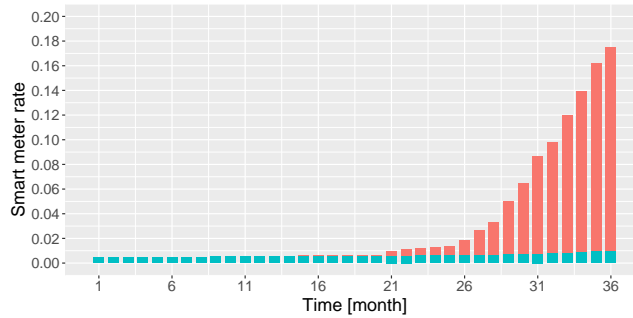


Figure 2: Monthly smart meter rate in the area (2016-2018).

324 The self-meter reading is indicated by a dummy variable (*self.read*), based on bimonthly obser-
 325 vations. The advantage for consumers is that they avoid estimated invoices, which must be adjusted
 326 after the official meter reading. Furthermore, sellers usually provide a discount for each self-reading.
 327 The issue will be less relevant with the spread of smart meters and real consumption billing without
 328 the need for supplementary reading by users or suppliers.

329 The classification of manufacturing activities (*prod*) is relevant for the non-household cluster, where
 330 it is a dummy indicating whether a given activity uses natural gas for production purposes. The
 331 information is obtained from consumers' declarations in the database of the provider. The gas
 332 sample used in the following models includes 650 users who declared that the natural gas is used
 333 both for heating and production purposes. Hence, a linear regression can be expected to highlight
 334 a significant increase in consumption for users with this particular feature.

335 Macro trends

336 In the sample, there are differences between consumers in heating area, GDP, quality of construc-
 337 tion, and demographics. Therefore, we studied some relevant macro trends for each specific local
 338 administration. These data were applied to the regression models, to partially adjust the lack of
 339 individual information in the data-set. As macro trends, we adopt average per capita gross income,
 340 average size of the home, the building-age index, and the population dependence index. Details of
 341 annual average gross income (*gross.income*) for each ZIP code were collected from the Italian Min-
 342 istry of Finance website.⁵ There are two possible benefits from using the average income parameter
 343 in the panel data regression. First, the parameter may be useful to mitigate the absence of income
 344 information, which is only partially satisfied by social welfare aid (*welf.aid*). Second, it can be
 345 interpreted as the variation in general economic welfare in the areas of interest over time and space.
 346 Therefore, we expect to find a positive correlation between natural gas demand and average income.
 347 Indeed, with a positive variation in economic well-being, an increase in consumption is desirable.
 348 Individual information on the size of the home is a fundamental parameter for natural gas con-
 349 sumption, but unfortunately, it was not available in the billing and distribution data. We therefore
 350 decided to use the average surface area parameter (*av.s.dwell*) to mitigate the absence of individual

⁵Italian Ministry of Finance. Italian gross income pro-capite data per ZIP code. <https://www1.finanze.gov.it/>. Last accessed: September 2022.

351 information. Moreover, the parameter can be useful to support the *n.dwell* variable in approxi-
 352 mating the home heterogeneity over the sample. The *av.s.dwell* is constant over time for each ZIP
 353 code, and it was obtained from the 2011 ISTAT survey.⁶

354 The building-age index (*build.age.index*) represents the building renovation ratio. Like the size
 355 of the home, it is a fundamental parameter for natural gas consumption. Recently renovated build-
 356 ings are expected to require significantly lower natural gas for heating. The index was calculated
 357 from the 2011 ISTAT database.⁷ It is the ratio between the number of buildings less than 20 years
 358 old and the number of buildings over 20 years old in 2011. It was determined for each ZIP code,
 359 and was constant over time.

360 The population dependence index (*dep.index*) represents the social and economic burden of the
 361 non-active population (0-14 years of age and 65 and over) on the active population (15-64 years
 362 of age). For example, in 2017 in Vicenza, there were 57.26 dependent individuals for every 100
 363 inwork. The data vary annually and spatially over the ZIP codes. The data were collected from the
 364 Open-Data archive of the Veneto region.⁸

365 3.2 Model Specification

366 This section describes the implementation of the empirical models adopted to study natural gas
 367 consumption patterns and the price elasticity of demand.

368 Relying on the existing literature, we implement the models in the double logarithmic form for the
 369 price, directly studying the elasticity, and in a log-linear form for the other variables. The models
 370 are based on the assumption that energy consumption, for individuals, is principally influenced by
 371 four factors (see table 2): price variations (*p*), weather variations (*w*), end-user characteristics (*d*),
 372 and social-economics factors (*e*). Therefore, the basic equation that drives the proposed models is:

$$\ln(Q_{i,t}) = \alpha \ln(p_{i,t}) + \beta w_{r,t} + \gamma d_{i,t} + \phi e_{r,t} + \lambda q_t + c_i + u_{i,t} \quad (2)$$

373 where α , β , γ , and ϕ are the matrices of the regression parameters and c_i and $u_{i,t}$ are the individual
 374 unobserved effect and the idiosyncratic error, respectively. We also included a quarter dummy q_t ,
 375 which indicates whether the observations are in the 1st, 2nd, 3rd, or 4th quarter of the year. The
 376 subscripts i , r , and t indicate individual, regional (characteristic of each ZIP code), and temporal
 377 variability, respectively.

378 When dealing with panel models, serial correlation and heteroskedasticity in the idiosyncratic error
 379 terms are problems that must be considered. The results of the Breusch Pagan (Breusch and Pagan,
 380 1979) and Wooldrich tests (Wooldridge, 2002) suggest that the sample is affected by both, then we
 381 use cluster-robust covariance matrix estimators.

382 Another important issue that can affect estimation quality is endogeneity misidentification. Many
 383 papers have studied energy demand-price elasticity; however, only a few have dealt with this ques-
 384 tion, providing potential bias. We treat the topic explicitly, trying to overcome the problem in the

⁶Censimento della popolazione e delle abitazioni, 2011, <https://www.istat.it/it/censimenti-permanenti/censimenti-permanenti>. Last access: May 2022.

⁷ISTAT, Censimento della popolazione e delle abitazioni 2011

⁸Regione Veneto, Open data Veneto, <https://dati.veneto.it>.

385 models illustrated below.

386 In particular, starting from equation 2, three sources of potential endogeneity might affect the
387 estimation:

388 1. The first concerns the natural gas price, which can suffer from simultaneity in the classical
389 theory of price-demand equilibrium. The error term variation can shift the demand curve,
390 inducing a variation in the equilibrium price.

391 This kind of endogeneity is the weakest form in this empirical research for two reasons. First,
392 ARERA settles the price structure quarterly in Italy before the start of the period itself. The
393 possible bias in the estimation can be induced by the projection of consumption presumed by
394 ARERA in the price decision process.

395 Second, we analyze micro panel data, where single consumers cannot shift the price curve
396 constructed for northern Italy. Therefore, the influence of our sample demand can be consid-
397 ered negligible in price construction, especially for CPM consumers. The endogeneity problem
398 could arise significantly in the FM group; indeed, the selling price is settled by sellers and
399 depends on several factors such as the type of end-user and the market price. However, as
400 seen above, prices for CPM and FM differ slightly in the period 2016-2018.

401 2. The second source is due to the specific structure of distribution and system charges, which
402 are direct functions of demand.

403 The price as a demand function is the most dominant form of endogeneity affecting price
404 elasticity with an upward bias. This type of endogeneity is dealt with in all the models
405 illustrated in the following subsections.

406 3. The third source concerns the omitted-variable problem, which occurs when relevant variables
407 correlated with the other explanatory variables are omitted. In this case, the error terms are
408 correlated with the dependent and explanatory variables, and the regression becomes biased
409 and inconsistent.

410 The easiest way to handle the problem is to use the fixed-effect method, eliminating the bias
411 when the omitted variables are constant over time. However, some relevant non-time constant
412 variables could have been omitted (e.g., household income, industrial production, number of
413 appliances, etc.). To overcome, or at least mitigate, this lack of basic individual information,
414 we utilize the information as macro trends instead of individual variables. Moreover, quarter-
415 indicator dummies are used in the models. These dummies are essential to capture different
416 individual behavior over the year. For example, heating systems are usually active only in the
417 1st and 4th quarters. 3rd quarter consumption is low due to the summer both for households
418 and non-households. Furthermore, Italy's price structure is established quarterly so a quarter
419 dummy is required in order to capture some in-year quarter seasonality that may affect price
420 elasticities.

421 Studying the model of equation 2, without accounting for endogeneity issues, the price-demand
422 elasticity results to be positive⁹, suggesting that the second and third types of endogeneity (the

⁹Respectively 0.428 and 0.55 for fixed effect (within estimator) and random effect methods (Swamy and Arora estimator).

price function of consumption and omitted variables) are primary problems.
 The following subsection sets out a theoretical description and the estimation results of the models.
 The sample is clustered into two groups: “Households” and “Non-households”. The models are built
 following the indication of the textbooks of Wooldrich (Wooldridge, 2002), and Baltagi (Baltagi,
 2005). Data processing is carried out with R statistical software following Croissant and Milo
 (Croissant and Millo, 2018).
 To improve the interpretation of results presented in the next section, variables related to weather,
 characteristics of houses, and macro trends (except dummies) have been standardized.

4 Results and Discussion

4.1 Model 1

The easiest way to overcome the endogeneity problem is to eliminate the natural gas distribution
 price component (*price.dis*), which is a direct function of consumption, and retain only the selling
 price component (*price.sel*). Indeed, *price.sel* may be slightly affected by the simultaneity problem,
 although it is not a demand function.

Simultaneity is considered a marginal problem both for CPM and FM consumers. For the CPM,
 the sales price is established a priori quarterly by ARERA. The *price.sel* is calculated based on
 spot prices and other macroeconomic trends. Therefore, the influence of individual demand on
 price is considered negligible. For the FM, the *price.sel* is the result of a direct agreement between
 consumers and the utility. However, FM and CPM prices slightly differ.

To sum up, in *Model 1*, we accept the bias introduced by the weak simultaneity problem between
 the *price.sel* and natural gas quantity. Nevertheless, we eliminate the reverse selection problem
 derived from *price.dis* that is omitted from the model.

To compare price elasticities from different methods, we estimate the model with the two classical
 panel model techniques that account for individual unobserved effects: fixed effects (FE) and ran-
 dom effects (RE). Table 4 shows the results of *Model 1* for individuals classified as households and
 non-households. Price elasticity is represented by the coefficient of the component *price.sel*.

The results of table 4 for the household group indicate that price elasticity is in the low range ob-
 served in the existing literature. However, we are unable to observe the elasticity of the distribution
 in the total natural gas price. Hence the elasticity is lower in magnitude than expected.

In the non-household group, the results deviate downward compared to the household group, con-
 firming past outcomes in the literature, i.e., non-residential users result to be less responsive to price
 variations than residential users.

4.2 Model 2

Model 2 explicitly resolves the endogeneity problem using the instrumental variables method that
 achieves consistent estimations when there is a correlation between the idiosyncratic error and the
 explanatory variables. In particular, the regressor *price.tot* is mainly affected by the second type of
 endogeneity, a demand function for the *price.dis* component. The within estimator can wipe out

	Model 1			
	Households		Non-households	
	FE (1)	RE (2)	FE (3)	RE (4)
ln(price.sel)	-0.3393*** (0.0055)	-0.3206*** (0.0055)	-0.1761*** (0.0352)	-0.2233*** (0.0343)
hdd	0.4879*** (0.0015)	0.4883*** (0.0015)	0.4610*** (0.0086)	0.4609*** (0.0085)
hum	-0.0199*** (0.0005)	-0.0193*** (0.0005)	-0.0055 (0.0030)	-0.0053 (0.0030)
rain	-0.0014* (0.0006)	-0.0020*** (0.0006)	-0.0114** (0.0035)	-0.0130*** (0.0035)
wind	-0.0106*** (0.0012)	-0.0120*** (0.0012)	-0.0091 (0.0087)	-0.0160 (0.0087)
winter	0.0044 (0.0028)	0.0044 (0.0028)	0.1170*** (0.0164)	0.1196*** (0.0164)
rain:winter	0.0038*** (0.0008)	0.0038*** (0.0008)	0.0046 (0.0050)	0.0063 (0.0050)
winter:wind	0.0685*** (0.0020)	0.0698*** (0.0019)	0.0651*** (0.0150)	0.0708*** (0.0149)
n.dwell		-0.1910*** (0.0040)		-0.1558*** (0.0330)
smart.meter	-0.1989*** (0.0046)	-0.1980*** (0.0045)	-0.1726*** (0.0315)	-0.0150 (0.0317)
self.read	-0.0527*** (0.0046)	-0.0537*** (0.0045)	-0.0055 (0.0652)	0.4264*** (0.0946)
av.s.dwell		0.0428*** (0.0038)		0.0055 (0.0350)
build.age.index		-0.0975*** (0.0051)		-0.1008* (0.0403)
welf.aid		-0.0280 (0.0150)		
prod				1.2687*** (0.0635)
free.market	0.0297*** (0.0037)	0.0335*** (0.0034)	-0.1258 (0.0842)	0.1195 (0.0993)
gross.income	0.0533*** (0.0022)	0.0341*** (0.0020)	0.0568*** (0.0138)	0.0100 (0.0129)
dep.index	-0.1711*** (0.0066)	-0.1380*** (0.0048)	-0.1759*** (0.0444)	-0.1926*** (0.0354)
q1	0.0034 (0.0018)	0.0050** (0.0018)	0.0490*** (0.0092)	0.0572*** (0.0092)
q2	-0.2788*** (0.0028)	-0.2735*** (0.0028)	-0.2373*** (0.0199)	-0.2262*** (0.0198)
q3	-0.5086*** (0.0030)	-0.5056*** (0.0030)	-0.4174*** (0.0186)	-0.4124*** (0.0186)
R ²	0.5603	0.5537	0.4778	0.4718
Adj. R ²	0.5477		0.4627	
Num. obs.	1,769,616	1,769,616	72,756	72,756
Hausman test	400.39 ($p < 0.001$)		802.3 ($p < 0.001$)	

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table 4: Model 1 results for household and non-household groups. Dependent variable: logarithmic monthly natural gas consumption ($\ln(Q)$). Clustered standard errors in ().

460 the individual effect c_i ; however, the correlation between the idiosyncratic error and the explanatory
461 variables remains. Therefore, the fixed effect estimator in table 4 is biased and inconsistent.

462 The problem can be solved by breaking the endogenous link between individual price and demand,
463 instrumenting the natural gas price. The standard approach is to specify a set of instruments cor-
464 related with the independent variables but uncorrelated with the idiosyncratic errors. To make the
465 estimation, we apply the *2SLS* technique.

466 We applied the *2SLS* technique in the panel models via two different estimators. The first is the

467 within-2SLS estimator (*W2SLS*), which transforms the estimation model, deviating from individ-
 468 ual means, wiping out the individual effects c_i . The *W2SLS* is consistent with simply exogenous
 469 instruments (the individual effect is correlated with the covariates). However, it is inefficient with
 470 doubly exogenous variables (no correlation between individual effects and covariates). Furthermore,
 471 it does not take into account the effects of time-invariant factors.

472 The second possibility is to consider the error component instrumental variables estimator (*EC2SLS*).
 473 This procedure was developed by Baltagi (Baltagi, 1980) (Baltagi, 1981), who applied the GLS es-
 474 timator to produce consistent and efficient results with double exogenous instruments.

475 In both models the number of external instruments must be at least equal to the number of endoge-
 476 nous covariates.

477 We applied these techniques utilizing two different sets of instruments. In the first (IV1), the
 478 *price.tot* is regressed in the first stage with the wholesale-market price of natural gas. For the
 479 second (IV2), we used the baseline prices published by ARERA.

480 **IV1** The external instrument used in the first instrumental model is the monthly mean of the
 481 natural gas price in the Italian wholesale market. This market is managed by GME (the
 482 Energy Services Manager), a public company owned by the Italian Ministry of the Economy
 483 and Finance.

484 In particular, we develop the estimation using the Intra-Day Gas Market price (*mi.gas*) as an
 485 instrument. It is calculated as the equilibrium price between natural gas supply and demand
 486 reflected in daily contracts.

487 The drawback of this instrument is that it does not explain distribution price elasticity. Indeed,
 488 only the selling price is correlated with the wholesale market price. Distribution is an entirely
 489 independent sector, where prices are based on the infrastructure investments carried out by
 490 Italian utilities.

$$\ln(\text{price.tot}_{i,t}) = \beta x_{i,t} + \zeta_1 \ln(\text{mi.gas}_t) + u_{i,t} \quad (3)$$

491 Equation 3 shows the first stage of the *2SLS*. Vector x represents the exogenous variable
 492 described in the base model (equation 2). We used the *mi.gas* price as external instrument.
 493 The latter two factors can regress respectively yearly macro trends and spatial variations that
 494 could affect the gas price.

495 **IV2** The second instrumental model is constructed from a simulated price calculated with the
 496 baseline prices of selling, distribution, and system changes. The baseline price is what an
 497 individual pays for the first unit of natural gas.

498 The simulated price breaks the endogeneity for both the selling and distribution components;
 499 therefore, we expect price elasticity larger in magnitude than *Model 1* and *Model 2.IV1*.

500 The drawback of baseline prices is that they do not explicitly consider the block tariff system.
 501 In fact, the model does not consider the change in prices when consumers exceed a specific
 502 block.

$$\ln(\text{price.tot}_{i,t}) = \beta x_{i,t} + \xi_1 \ln(\text{sel.base}_t) + \xi_2 \ln(\text{dis.base}_t) + u_{i,t} \quad (4)$$

503 Equation 4 shows the first stage of the *2SLS*. The *sel.base* (the sales cost portion of the

504 baseline price) and *dis.base* (distribution part of the baseline price) factors are the external
 505 instruments.

	<i>Model 2.IV1</i>				<i>Model 2.IV2</i>			
	Households		Non-households		Households		Non-households	
	W2SLS (1)	EC2SLS (2)	W2SLS (3)	EC2SLS (4)	W2SLS (5)	EC2SLS (6)	W2SLS (7)	EC2SLS (8)
ln(price.tot)	-0.2872*** (0.0164)	-0.2339*** (0.0270)	0.0580 (0.0731)	0.0066 (0.1031)	-0.5098*** (0.0088)	-0.4769*** (0.0148)	-0.4383*** (0.0507)	-0.4584*** (0.0714)
hdd	0.4821*** (0.0017)	0.4851*** (0.0029)	0.4689*** (0.0091)	0.4674*** (0.0131)	0.4690*** (0.0015)	0.4707*** (0.0026)	0.4451*** (0.0087)	0.4449*** (0.0125)
hum	-0.0175*** (0.0005)	-0.0171*** (0.0009)	-0.0044 (0.0030)	-0.0044 (0.0043)	-0.0181*** (0.0005)	-0.0176*** (0.0009)	-0.0048 (0.0030)	-0.0046 (0.0043)
rain	-0.0035*** (0.0006)	-0.0043*** (0.0010)	-0.0137*** (0.0034)	-0.0147** (0.0050)	-0.0009 (0.0006)	-0.0015 (0.0010)	-0.0097** (0.0035)	-0.0108* (0.0050)
wind	-0.0116*** (0.0012)	-0.0131*** (0.0020)	-0.0114 (0.0088)	-0.0149 (0.0126)	-0.0093*** (0.0012)	-0.0107*** (0.0020)	-0.0068 (0.0088)	-0.0109 (0.0126)
winter	0.0233*** (0.0034)	0.0178** (0.0059)	0.1066*** (0.0174)	0.1108*** (0.0252)	0.0482*** (0.0030)	0.0452*** (0.0052)	0.1461*** (0.0172)	0.1483*** (0.0247)
rain:winter	0.0070** (0.0008)	0.0071** (0.0014)	0.0058 (0.0050)	0.0072 (0.0072)	0.0065*** (0.0008)	0.0064*** (0.0014)	0.0054 (0.0050)	0.0066 (0.0072)
winter:wind	0.0759*** (0.0020)	0.0763*** (0.0034)	0.0681*** (0.0149)	0.0714*** (0.0216)	0.0775*** (0.0020)	0.0782*** (0.0034)	0.0665*** (0.0150)	0.0702** (0.0216)
n.dwell		-0.1934*** (0.0069)		-0.1746*** (0.0491)		-0.1946*** (0.0070)		-0.1722*** (0.0486)
smart.meter	-0.2202*** (0.0048)	-0.2224*** (0.0081)	-0.1966*** (0.0319)	-0.1143* (0.0456)	-0.1991*** (0.0046)	-0.1989*** (0.0078)	-0.1608*** (0.0317)	-0.0796 (0.0450)
self.read	-0.0532*** (0.0046)	-0.0538*** (0.0077)			-0.0524*** (0.0047)	-0.0533*** (0.0077)		
av.s.dwell		0.0400*** (0.0064)		0.0114 (0.0525)		0.0442*** (0.0065)		0.0213 (0.0523)
build.age.index		-0.0824*** (0.0088)		-0.0477 (0.0621)		-0.0994*** (0.0090)		-0.1327* (0.0624)
welf.aid		-0.0252 (0.0259)				-0.0248 (0.0262)		
prod				1.3855*** (0.0952)				1.3431*** (0.0930)
free.market	0.0201*** (0.0038)	0.0223*** (0.0059)	-0.1330 (0.0780)	0.1165 (0.1270)	0.0319*** (0.0037)	0.0350*** (0.0059)	-0.1283 (0.0862)	0.1352 (0.1331)
gross.income	0.0380*** (0.0024)	0.0200*** (0.0036)	0.0229 (0.0144)	-0.0019 (0.0195)	0.0586*** (0.0023)	0.0398*** (0.0035)	0.0807*** (0.0143)	0.0497** (0.0191)
dep.index	-0.1406*** (0.0068)	-0.1157*** (0.0084)	-0.0892* (0.0453)	-0.1268* (0.0549)	-0.1738*** (0.0068)	-0.1439*** (0.0085)	-0.2377*** (0.0461)	-0.2447*** (0.0558)
q1	-0.0245*** (0.0024)	-0.0178*** (0.0040)	0.0559*** (0.0104)	0.0566*** (0.0149)	-0.0482*** (0.0019)	-0.0434*** (0.0033)	0.0162 (0.0097)	0.0196 (0.0139)
q2	-0.2692*** (0.0036)	-0.2589*** (0.0060)	-0.2043*** (0.0212)	-0.2016*** (0.0303)	-0.3046*** (0.0029)	-0.2972*** (0.0050)	-0.2742*** (0.0199)	-0.2667*** (0.0285)
q3	-0.5060*** (0.0034)	-0.4988*** (0.0057)	-0.3940*** (0.0196)	-0.3941*** (0.0282)	-0.5328*** (0.0031)	-0.5279*** (0.0052)	-0.4463*** (0.0186)	-0.4430*** (0.0267)
R ²	0.5567	0.5517	0.4781	0.4743	0.5544	0.5487	0.4716	0.4681
Adj. R ²	0.5443		0.4630		0.5416		0.4564	
Num. obs.	1,769,616	1,769,616	72,756	72,756	1,769,616	1,769,616	72,756	72,756
Hausman test	288.49 ($p < 0.001$)		345.53 ($p < 0.001$)		447.01 ($p < 0.001$)		342.42 ($p < 0.001$)	

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table 5: *Model 2* results. The natural gas price is instrumented with external instruments. Clustered standard errors in ().

506 For the household group, in *Model 2.IV1*, the price elasticity *price.tot* values are akin to those in
 507 *Model 1*. Indeed, the wholesale price instrument (*mi.gas*) can explain only the selling portion of
 508 the total price (*price.tot*). As in *Model 1*, the price component observed in the elasticity is the
 509 selling price. The instrument ignores distribution and system-charges, which continue to generate

510 endogeneity, decreasing the elasticity of the model in absolute terms.

511 In *Model 2.IV2*, the elasticity coefficients (*price.tot*) represent the sum of the *price.sel* and *price.dis*
 512 components. Therefore, they are larger than in *Model 1* and *Model 2.IV1*. *Model 2.IV2* results
 513 for non-households confirm the result found for *Model 1* where elasticity is weaker than in the
 514 household group. Furthermore, in *Model 2.IV1*, the price variation has no significance, indicating
 515 the negligible effect of price variations in production or commercial activities.

516 4.3 Discussion of Results

517 The study of price elasticity is the heart of this empirical study. The results show that price
 518 elasticity is negative, as expected, for all the models illustrated in the previous section. According
 519 to the literature, consumers react negatively to price variation, although the price-demand dynamic
 520 is mostly inelastic, at less than 1. This means that natural gas price changes have less impact on
 521 consumption than other factors. Table 6 summarizes price elasticities as found in the models.

	<i>Model 1</i>	<i>Model 2.IV1</i>	<i>Model 2.IV2</i>
Households	-0.32 ~ -0.34	-0.23 ~ -0.29	-0.48 ~ -0.51
Non-households	-0.18 ~ -0.22	-	-0.44 ~ -0.46

Table 6: Summary of natural gas price elasticities.

522
 523 The household group results indicate that a 1% increase in natural gas price reduces residential
 524 consumption in the range of 0.23 ~ 0.51%. This is consistent with past empirical studies, as illus-
 525 trated in section 2.

526 The result of the non-household group is generally lower in magnitude, and the elasticity found in
 527 *Model 2.IV1* is not significant. The literature (Labandeira et al., 2012) confirms that price varia-
 528 tions impact less on demand in production and commercial activities. However, in our sample, the
 529 non-household group is heterogeneous and includes several consumption profiles that may react to
 530 price changes.

531 In our opinion, natural gas use in commercial or industrial activities is marginally influenced by
 532 price changes, mostly when energy efficiency programs are ignored. However, the non-residential
 533 sample is cross-sectionally much smaller and more heterogeneous than the household group. This
 534 may lead to bias estimations caused by outlier data.

535 Based on the price analysis and the increase in endogeneity, we expected different elasticities from
 536 the models and demonstrate that price elasticity evolves in function of how the endogeneity is
 537 treated.

538 For instance, considering the residential demand, in *Model 1* and *Model 2.IV1*, endogeneity is par-
 539 tially considered. These models exploit only the *price.sel* component of the total price, with the
 540 lowest elasticity values in the $-0.23 \sim -0.34$ range. In *Model 2.IV2*, the aim is to fully break the
 541 endogeneity of *price.tot*. The elasticity is larger, indicating that the residential response to a price
 542 change is in the range between -0.5 .

543

544 The signs of environmental variables meet our expectations. As previous empirical work has
545 pointed out, the main variable of interest for natural gas consumption is temperature. The *hdd* is
546 the main driver of our empirical models. The variable aims to capture the seasonality of natural
547 gas consumption, both for residential and non-residential users. In particular, an increase in *hdd*
548 values involves a reduction in daily mean temperature and an increase in heating. It is also worth
549 noting that *wind* and *rain* factors are correctly positively correlated with gas demand; indeed,
550 both cause more heat loss. However, the coefficient magnitude is dominant for the *hdd*. The other
551 environmental factors are at least one order of magnitude lower. Especially *rain* and *hum* effects
552 are non-significant at almost zero. For the non-household sample, the *hdd* and *wind* are the only
553 two significant weather factors. Weather results have no significant differences between the various
554 static methods and groups.

555
556 Home characteristics are important factors for residential natural gas consumption. In partic-
557 ular, in northern Italy, the most common heating source is natural gas. The size of the home,
558 construction materials, and type of appliances are essential information significantly influencing en-
559 ergy demand. Unfortunately, this information is not available in our data sets. Therefore, we sought
560 to mitigate the omitted variable effects with several dummies and socioeconomic macro trends.
561 The number of homes in the same building (*n.dwell*) is obtained from the address information in
562 the distribution data set. To the best of our knowledge, this variable is tested for the first time. We
563 started from the assumption that single houses are generally larger with more heat loss. The results
564 confirm this hypothesis, relating natural gas demand negatively with the *n.dwell* variable in all the
565 models. This factor is also relevant to the non-household group, probably due to the commercial
566 activities in the sample with similar characteristics to the residential group.
567 The macro trends of home characteristics are meaningful, especially for households. The variation
568 of the average size of the home (*av.s.dwell*) and the building age index (*build.age.index*) accurately
569 show that areas with larger and newer homes consume respectively more and less natural gas.
570 Another significant factor in the regressions is the *smart.meter*, used to read consumption. The
571 main reason for installing smart-metering technology with end-users is to guarantee billing based on
572 actual consumption and not on estimates. Estimated bills must be adjusted in subsequent invoices
573 after an actual reading, so bills do not reflect real consumption. As observed by Gans et al. (Gans
574 et al., 2013), the provision of the additional information by smart-meters reduces energy consump-
575 tion (natural gas in our case) by end-users. Consumers with accurate billing invoices can check and
576 adjust their consumption. The negative sign for the smart-metering dummy is consistent with this
577 assumption. Furthermore, the issue has been extensively studied in the electricity market (Schleich
578 et al., 2012) (Carroll et al., 2014), with similar results.
579 Similarly, the self-reading dummy (*self.read*) should be considered, negatively correlating with nat-
580 ural gas demand. The self-reading of gas meters produces accurate billing invoices that do not need
581 future adjustments by providers (except for reading errors by end-users). Furthermore, consumers
582 who read their own meters are likely to be more aware of, and sensitive, to cost.

583
584 The socioeconomic factors considered for the residential cluster are: macro trends indicating

585 yearly gross income per capita and dependent population index (*gross.income* and *dep.index*), the
586 market-liberalization dummy (*free.market*), and the indication of low-income households (*welf.aid*).
587 For the non-household group, the low-income indicator (relevant only for households) is replaced
588 by the dummy variable *prod*, indicating whether natural gas is also used for manufacturing.
589 The macro trends introduce the spatial variability of the sample; since the data are annual, tem-
590 poral variability is limited. The resulting signs are consistent with our expectations. The income
591 indicator (*gross.income*) is positive; locations with high incomes are assumed to consume more
592 energy. The *dep.index* is negative, indicating that the population tends to consume more in the
593 working-age. Finally, macro trends can be useful to mitigate the lack of individual information; the
594 influence of these socioeconomic variables is small but significant.
595 The dummy (*welf.aid*) shows that the population that received energy welfare subsidies in 2016-
596 2018 tends to consume slightly less than the rest of the sample. However, the difference is small in
597 all the models, indicating that the effect is limited. A similar consideration applies to the liberaliza-
598 tion process dummy (*free.market*), where the magnitude does not indicate a substantial difference
599 between free-market and CPM users. Furthermore, the positive sign of the residential group indi-
600 cates that market deregulation does not influence consumer sensitivity to energy consumption. This
601 result is consistent, for example, with the paper of Nakajima et al. (Nakajima and Hamori, 2010)
602 who found no substantial difference in price elasticity between deregulated and non-deregulated
603 states in the US.

604
605 Finally, the research on price elasticity might have several practical implications. For instance,
606 we have observed how households react to price changes in the study area. A significant increase in
607 prices would lead households to use energy more efficiently. This can be particularly useful for local
608 policymakers, especially in the short term when a reduction in energy consumption is necessary.
609 In the area of study is fundamental to study proper administrative tools to restrict the level of
610 emissions¹⁰. Furthermore, from our results, the level of technological innovation in the energy
611 grid (*smart.meter* and *self.read* dummies) has a clear influence on residential gas consumption.
612 This factor could be exploited by energy authorities for a long-term demand reduction, stimulating
613 awareness of energy consumption in the population.

614 Our results could be important for energy utilities, as well. The use of price elasticity can be
615 a useful tool to forecast companies' revenues or to design energy scenarios. The topic is nowadays
616 particularly important due to the huge volatility of spot and forward natural gas and electricity
617 prices that can significantly influence the evolution of local energy demand and, consequently,
618 utilities' revenues. Furthermore, we have shown how companies and large consumers are hardly
619 affected by the variations in prices, with elasticities always lower than residential end-users. This
620 information could be useful to set proper price policies.

621 The study of price elasticity can also be a fundamental tool to design proper regulations and
622 incentives. For example, (Xiang and Lawley, 2019) estimate the effects of the 2008 carbon tax in
623 the British Columbia on residential natural gas consumption per capita. Implementing a panel data

¹⁰Vicenza air quality is classified on average as "poor" by European Environment Agency.
<https://www.eea.europa.eu/themes/air/urban-air-quality/european-city-air-quality-viewer>

analysis, they use several input variables with data from 1990 to 2014, such as gas demand, weather conditions, fuel prices, building and population characteristics. Their results suggest that factors such as weather and household characteristics have a crucial impact in the short and medium-term, compared to gas and household incomes. However, they are able to assess the long-term impacts of a carbon tax. The overall results suggest that a carbon tax of 1 cent/m³ reduces per capita natural gas consumption by 3%. Hence, the result can be interpreted as negative price-demand elasticity. In a very recent paper, (Liu et al., 2022) study the effect of a carbon tax on the demand of several fuels in China. The paper explores the influence that energy price increases implied by a carbon tax has on the on fuel consumption using a quadratic almost ideal demand system (QUAIDS) model. According to the output of the estimated model, the authors state the impact of carbon tax on natural gas is neutral at aggregate national level and in urban areas, while a negative progressive elasticity is observed in rural areas. Price elasticity of energy consumption could have policy implications in the field of energy efficiency. The effect of a carbon tax on energy efficiency has been indeed studied by (Adetutu et al., 2020). The methodology applied by the authors relies on a procedure for the decomposition of the energy intensity based on a stochastic energy frontier. They collect data on a sample of firms in UK and find that the impact of a carbon tax on energy efficiency is lower than the substitution effect among fuels.

5 Conclusion

This paper shows how consumers respond to price variations when the authorities liberalize the retail energy sector. In particular, we focus on natural gas, which will be fundamental in the near future for local strategies regarding energy demand and decarbonization.

In the Italian sector, household natural gas consumption deserves the attention of policymakers, since it is the primary thermal energy source. During the period of analysis, households had few alternatives to natural gas for heating. Indeed, the electricity is generally much more expensive than natural gas and the district heating networks are limited in extension. In 2013, natural gas was the primary source for residential heating (72.3 %) in the Veneto region. Electricity was used for heating only by the 1.5 % of households ¹¹. However, in recent years, structural and plant redevelopment of residential buildings have been encouraged by the Italian government. This should lead to an increasing use of heating pumps for domestic hot water (33.3 % of new buildings) and heating (40 % of new buildings) (Regione Veneto, 2017).

The international literature includes numerous empirical cases investigating the factors driving energy consumption. However, natural gas distribution is studied marginally compared to electricity, especially when disaggregated data are available.

To the best of our knowledge, our paper includes the first application of panel models to Italian natural gas billing data at the individual level. Considering this kind of data, we adopt a bottom-up statistical approach analyzing each individual contribution and studying the principal economic and environmental drivers. Similar techniques have been applied in other countries (see section 2); however, our analysis distinguishes itself due to the integration of billing and distribution data

¹¹ISTAT, 2013. Consumi energetici delle famiglie, <http://dati.istat.it/Index.aspx?QueryId=22809>

662 (which are usually private and difficult to obtain), as well as weather factors. Furthermore, we
663 analyze the different types of endogeneity in the price-demand relationship in detail, suggesting
664 possible statistical solutions.

665 Previous analyses regarding the Italian case never combined disaggregated micro-data (i.e., billing
666 data) with elasticity estimation. For instance, Besagni et al. (2018) use disaggregated data, but
667 not billing data, and do not estimate price elasticities. On the other hand, Bianco et al. (2014)
668 estimate price elasticities applying a top-down approach without using billing data.

669 Given the local nature of the data, our study is initially of local interest in the area of Vicenza
670 in northern Italy but turns out to have widespread policy implications. The Veneto region is the
671 core of Italian manufacturing with a primary role in national energy consumption. Moreover, our
672 methods transcend spatial and temporal limitations and can be applied in any region or country.
673 To study natural gas price elasticity and consumption patterns, we assembled three-panel data mod-
674 els, collecting data from different sources in the period January 2016-December 2018: (1) monthly
675 billing data, (2) weather factors, (3) technical distribution data, and (4) macro socioeconomic trends.
676 The billing and distribution data are interpolated using an identifier code for each end-user. The
677 weather factor and macro-trends relate to each ZIP code.

678
679 Macro-trends include average gross income (yearly variation), the average size of the home (fixed
680 over time), the building-age index (fixed over time), and the dependence-population index (yearly
681 variation). The combination of these factors with micro-data are useful to overcome the lack of
682 individual information in the data-set and mitigate the endogeneity effect due to the omitted vari-
683 able problem. The signs of regression coefficients are significant and coherent with our expectation
684 (e.g., wealthier areas with larger homes consume more natural gas.); however their magnitude is
685 generally lower than that related to other variables, such as the main drivers of gas consumption
686 (e.g., temperature), the presence of smart meters, the number of dwellings in the same building.
687 The panel models solves the increase in endogeneity with different methods. In *Model 1*, the price
688 component is a demand-function is eliminated. In *Model 2*, price elasticity as studied considering
689 instrumental variable methods. In particular, the wholesale market price and the baseline prices
690 established quarterly by ARERA are used as external instruments to break the price endogeneity.
691 Furthermore, in Appendix B, a dynamic panel data model is proposed with the first lag of nat-
692 ural gas consumption in the regressor matrix (this model is deeply analyzed in Favero’s doctoral
693 thesis(Favero, 2022)). Of the static models our preference is for fixed-effect methods because Haus-
694 man tests suggest a correlation between the individual fixed effect and the regressors, rendering RE
695 methods inconsistent. However, since the results are similar, we also used RE estimates to interpret
696 the factors fixed over time.

697 The results obtained from the models have the signs expected and are robust across the different
698 static models. However, the dynamic panel model defined in Appendix B has some inconsistencies
699 in correlation signs, indicating that the consumption lag in the explanatory variables significantly
700 affects the regression coefficients.

701 The estimates of price elasticity appear to be consistent across the various specifications and the
702 previous literature. The values are between -0.2 and -0.5 for households and -0.2 and -0.4 for

703 non-households, based on the level of endogeneity resolution. However, some price components are
704 unobserved in our investigation. Indeed, in addition to VAT, end-users have fixed costs irrespective
705 of gas consumption. Furthermore, end-users are subject to billing adjustments after the meter
706 reading and different invoice periods (monthly or bimonthly). Unfortunately, due to the specificity
707 of each end-user, it was not possible to construct a complete data-set including all the possible
708 cases.

709 The analyses and results illustrated in this paper should be interpreted with caution. We
710 estimated price elasticity in a relatively small area and for one utility only, as seller and distributor.
711 Therefore, the outcomes might be biased by the sample selection. The analysis can be considered
712 a reference point for the population of northern Italy but is less significant if the entire Italian
713 population is considered. Furthermore, Agsm Aim Energia Srl is the only source of billing data and
714 the data could therefore be affected by unobserved structural collection errors.

715 The large data-set (especially in the household group) and cluster standard errors ensure con-
716 sistency even in the presence of individual heterogeneity. Moreover, elasticity increases with the
717 endogeneity resolution level. This can be considered proof of the accuracy of the estimates. Of the
718 proposed models, *Model 2.IV2* is preferable, where the total price is instrumented directly from the
719 prices established by ARERA.

720 The dynamic model proposed in Appendix B deserves further study; in particular, the consump-
721 tion lag value seems to be a source of distortion, overestimating price elasticity and changing the
722 sign of other factors such as the use of a smart-meter and the effects of the wind and humidity.

723 The lack of individual information is mitigated in our models by using macro trends and quarter
724 dummies. Further research could integrate the billing and distribution data sets with a survey of
725 the individual characteristics of consumers. The significance level of macro trends confirms the im-
726 portance of home characteristics, income, and household composition. Furthermore, while we have
727 conducted a simple simulation of the effects of market liberalization during the current transition
728 phase, a more detailed analysis of liberalization will be possible when it has been completed. Simi-
729 larly, the spread of smart-metering technology should be analyzed in depth to study the implications
730 for consumers and exploit this possible new source of data.

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874 **Appendix A Robustness Check**

875 To test the robustness of the panel analysis, we carried out a robustness check excluding possible
 876 outliers from the estimation. Therefore, we filtered the PODs with natural gas consumption (Q)
 877 lower than the 1st percentile and higher than the 99th percentile. Then, we estimated the *Model 2*
 878 for the new data-set, comparing the results in tables A1 and 5. The difference in price elasticity is
 879 marked for Households in *Model2.IV2*, however, other coefficients and other models do not present
 relevant differences, suggesting a negligible effects of outliers.

	<i>Model 2.IV1</i>				<i>Model 2.IV2</i>			
	Households		Non-households		Households		Non-households	
	W2SLS (1)	EC2SLS (2)	W2SLS (3)	EC2SLS (4)	W2SLS (5)	EC2SLS (6)	W2SLS (7)	EC2SLS (8)
ln.price.tot	-0.2699*** (0.0164)	-0.2114*** (0.0280)	0.1068 (0.0685)	0.0708 (0.1047)	-0.6197*** (0.0095)	-0.5767*** (0.0164)	-0.4468*** (0.0508)	-0.4493*** (0.0772)
hdd	0.4436*** (0.0013)	0.4447*** (0.0024)	0.4526*** (0.0079)	0.4515*** (0.0124)	0.4349*** (0.0013)	0.4356*** (0.0023)	0.4406*** (0.0078)	0.4401*** (0.0121)
hum	-0.0129*** (0.0005)	-0.0128*** (0.0009)	-0.0008 (0.0028)	-0.0002 (0.0044)	-0.0106*** (0.0005)	-0.0102*** (0.0009)	0.0036 (0.0028)	0.0042 (0.0043)
rain	-0.0095*** (0.0007)	-0.0099*** (0.0013)	-0.0217*** (0.0042)	-0.0221*** (0.0066)	-0.0069*** (0.0008)	-0.0071*** (0.0013)	-0.0182*** (0.0042)	-0.0186** (0.0066)
winter	0.0974*** (0.0036)	0.0947*** (0.0064)	0.0185 (0.0203)	0.0232 (0.0318)	0.1147*** (0.0036)	0.1128*** (0.0063)	0.0558** (0.0197)	0.0576 (0.0308)
wind	0.0082*** (0.0017)	0.0074* (0.0030)	-0.0051 (0.0113)	-0.0081 (0.0177)	0.0068*** (0.0017)	0.0056 (0.0030)	-0.0064 (0.0114)	-0.0095 (0.0177)
rain:winter	0.0271*** (0.0009)	0.0270*** (0.0016)	0.0198*** (0.0052)	0.0199* (0.0082)	0.0262*** (0.0009)	0.0258*** (0.0016)	0.0171** (0.0053)	0.0171* (0.0082)
winter:wind	0.0102*** (0.0026)	0.0092* (0.0046)	0.0302 (0.0162)	0.0328 (0.0254)	0.0206*** (0.0026)	0.0204*** (0.0046)	0.0391* (0.0164)	0.0413 (0.0255)
n.dwell		-0.1371*** (0.0064)		-0.1840*** (0.0489)		-0.1381*** (0.0066)		-0.1817*** (0.0485)
smart.meter	-0.1955*** (0.0048)	-0.1983*** (0.0083)	-0.1535*** (0.0290)	-0.0829 (0.0453)	-0.1614*** (0.0046)	-0.1618*** (0.0081)	-0.1131*** (0.0290)	-0.0447 (0.0448)
self.read	-0.0568*** (0.0049)	-0.0580*** (0.0084)			-0.0557*** (0.0049)	-0.0572*** (0.0084)		
av.s.dwell		0.0368*** (0.0063)		0.0096 (0.0515)		0.0416*** (0.0064)		0.0165 (0.0516)
build.age.index		-0.0927*** (0.0089)		-0.0297 (0.0637)		-0.1205*** (0.0092)		-0.1306* (0.0649)
welf.aid		-0.0040 (0.0248)				-0.0040 (0.0253)		
prod				1.0906*** (0.0958)				1.0572*** (0.0938)
free.market	0.0219*** (0.0038)	0.0230*** (0.0062)	-0.1269 (0.0919)	0.0979 (0.1355)	0.0413*** (0.0038)	0.0431*** (0.0061)	-0.1252 (0.1036)	0.1129 (0.1436)
gross.income	0.0394*** (0.0024)	0.0230*** (0.0037)	0.0209 (0.0140)	-0.0029 (0.0204)	0.0692*** (0.0024)	0.0502*** (0.0037)	0.0790*** (0.0141)	0.0501* (0.0204)
dep.index	-0.1585*** (0.0070)	-0.1180*** (0.0085)	-0.0879* (0.0432)	-0.1145* (0.0559)	-0.2156*** (0.0072)	-0.1617*** (0.0088)	-0.2676*** (0.0448)	-0.2537*** (0.0578)
q1	0.0140*** (0.0025)	0.0182*** (0.0045)	0.1239*** (0.0128)	0.1273*** (0.0202)	-0.0028 (0.0025)	0.0011 (0.0045)	0.1073*** (0.0130)	0.1121*** (0.0203)
q2	-0.2294*** (0.0036)	-0.2221*** (0.0064)	-0.1962*** (0.0177)	-0.1908*** (0.0280)	-0.2653*** (0.0035)	-0.2592*** (0.0062)	-0.2309*** (0.0181)	-0.2241*** (0.0283)
q3	-0.4370*** (0.0046)	-0.4330*** (0.0082)	-0.3504*** (0.0242)	-0.3469*** (0.0382)	-0.4590*** (0.0047)	-0.4559*** (0.0083)	-0.3639*** (0.0244)	-0.3604*** (0.0382)
R ²	0.5624	0.5569	0.4781	0.4857	0.5576	0.5520	0.4777	0.4739
Adj. R ²	0.5499		0.4630		0.5450		0.4627	
Num. obs.	1,540,044	1,540,044	64,692	64,692	1,540,044	1,540,044	64,692	64,692

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table A1: *Model 2* results. The natural gas price is instrumented with external instruments. Clustered standard errors in ().

881 **Appendix B Dynamic Panel Model**

882 The models implemented in the main part of the paper are static; the correlation with past con-
 883 sumption has never been considered. A possible development is to implement a dynamic panel
 884 model characterized by delayed dependent variables within the regressor matrix (equation 5).

$$\ln(Q_{i,t}) = \theta \ln(Q_{i,t-1}) + \alpha \ln(p_{i,t}) + \beta w_{r,t} + \gamma d_{i,t} + \phi e_{r,t} + \lambda q_t + c_i + u_{i,t} \quad (5)$$

885 where θ is the parameter relating to the autoregressive component.

886 Implementing models with both individual effects and lagged dependent variables can signifi-
 887 cantly reduce omitted variable endogeneity.

888 As estimator we used the Blundell-Bond estimator (sys-GMM) (Blundell and Bond, 1998) (Arel-
 889 lano and Bover, 1995), an expansion of the classic Arellano-Bond estimator (GMM) (Arellano and
 890 Bond, 1991). The main reason for preferring the Blundell-Bond estimator is to limit weak instru-
 891 ments that can affect the classic Arellano-Bond approach. Furthermore, in our model, the number
 892 of times is sufficient (more than 10) to limit the number of instrument lags to 10, avoiding the
 893 propagation of weak instruments.

894 By construction, in GMM and sys-GMM models, residuals are affected by serial correlation of
 895 the first order; however, residuals should not exhibit a significant serial correlation of the second
 896 order.

897 Table B1 shows the results of the dynamic panel models. Unlike the previous models, the
 898 variables considered in the dynamic panel model exclude the macro trends and the constant dummies
 899 over time that cause singularities.

900 The regression coefficients confirm that residential is more responsive than non-residential con-
 901 sumption. Furthermore, the elasticities found with the sys-GMM estimator have a greater mag-
 902 nitude than the previous model. Unlike *Model 1* and *Model 2*, the use of a dynamic model can
 903 potentially entirely solve the endogeneity problem for both the price components (*price.sel* and
 904 *price.dis*) and for the block tariff system. Indeed, exploiting past consumption as an instrument
 905 can define individual consumption patterns, identifying past correlations between consumption and
 906 variations in the price as a demand function (the second type of endogeneity). However, other coef-
 907 ficients (e.g., *hdd*, *wind*, *smart.meter*) are different in magnitude and sign than the static models.
 908 It is reasonable to assume that the lag of gas consumption captures much of the variability, yielding
 909 less significant and possible inconsistent outcomes.

	<i>Model 3</i>	
	Households	Non-households
	sys-GMM (1)	sys-GMM (2)
lag(ln(Q), 1)	0.9226*** (0.0017)	0.9287*** (0.0104)
ln(price.tot)	-0.7404*** (0.0075)	-0.4695*** (0.0468)
hdd	-0.0030*** (0.0016)	0.0431*** (0.0088)
wind	-0.0450*** (0.0010)	-0.0445** (0.0058)
rain	0.00220*** (0.0005)	0.0216*** (0.0027)
hum	-0.0077** (0.0008)	0.0075*** (0.0042)
smart.meter	0.2111*** (0.0043)	0.1243*** (0.0224)
self.read	-0.0072* (0.0038)	
free.market	0.0299*** (0.0019)	0.2030*** (0.0285)
q1	-0.4547*** (0.0029)	-0.3666*** (0.0180)
q2	-0.8329*** (0.0041)	-0.6364*** (0.0247)
q3	-0.3868*** (0.0046)	-0.2370*** (0.0233)
Autocorrelation test (2nd order)	0.8037 ($p = 0.9359$)	0.4013 ($p = 0.6882$)
Num. obs.	1,769,616	72,756

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table B1: Dynamic Panel model with Blundell Bond estimator. Clustered standard errors in ().

The authors wish to acknowledge the time devoted by the Editor, Associate Editor and Reviewer#1 to the second review of the paper. Many thanks to Reviewer#1 for the new suggestions. The authors have taken them into account in the new revision of the manuscript. They think that the new version has improved the previous one and hope that the current version of the manuscript could be positively evaluated.

In this document comments made by Reviewer#1 are in italic font and the responses in normal font.

Reviewer #1: I am glad that many of the reviewers' comments have been addressed. However, I think the paper needs some more (minor) revisions before proceeding to a possible publication. In particular:

Point 1) Policies should be very specific and clear.

Section 4 has been expanded to include new more specific policy implications of our results. In particular, we have commented the results of the empirical analysis and suggested possible policy implications for the management of gas supply at the local level (see lines 605-623 of the new version).

Point 2) Regarding the updated Table 1, authors could take into account some of the following publications:

- *Filippini, M., & Kumar, N. (2021). Gas demand in the Swiss household sector. Applied Economics Letters, 28(5), 359-364.*

- *Kostakis, I., Lolos, S., & Sardianou, E. (2021). Residential natural gas demand: Assessing the evidence from Greece using pseudo-panels, 2012-2019. Energy Economics, 99, 105301.*

- *Alberini, A., Khymych, O., & Ščasný, M. (2020). Responsiveness to energy price changes when salience is high: Residential natural gas demand in Ukraine. Energy Policy, 144, 111534.*

- *Dong, K., Dong, X., & Sun, R. (2019). How did the price and income elasticities of natural gas demand in China evolve from 1999 to 2015? The role of natural gas price reform. Petroleum Science, 16(3), 685-700.*

- *Zhang, Y., Ji, Q., & Fan, Y. (2018). The price and income elasticity of China's natural gas demand: A multisectoral perspective. Energy Policy, 113, 332-341.*

Many thanks for these new references. We have included them in the reference list, with exception of "Alberini, A., Khymych, O., and Scasny, M. (2020)", which was already included in the previous version. We have updated Table 1 accordingly summarizing the main results contained in each paper.

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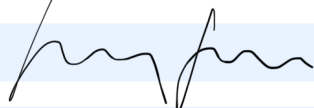
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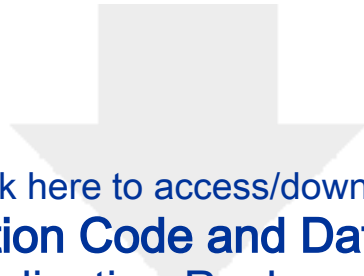
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