Green Car Adoption and the Supply of Alternative Fuels.

Job Market Paper

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Abstract

Easy availability of stations serving alternative fuels is an obvious concern for customers considering to buy a "green" car. Yet, the supply of fuel is seldom considered when analyzing the problem of fostering the adoption of environmentally friendly vehicles. I develop and estimate a joint model of demand for green cars and supply of alternative fuels. Customers care about the density of stations offering the fuel their car runs on in their market; stations only supply fuels whose stock of circulating cars is large enough to cover the fixed cost of building an alternative fuel pump. I use this framework to compare the effectiveness of a subsidy to consumers who buy cars running on alternative fuels to that of a subsidy to gas stations installing alternative fuel pumps. Counterfactual simulations suggest that subsidizing fuel retailers to offer alternative fuels is an effective policy to indirectly increase low emission car sales.

JEL Classification: H23, H25, L11, L91, Q48.

Keywords: Alternative fuel cars; Entry; Environmental policy.

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1 Introduction

Fostering the use of more environmentally friendly fuels, like Liquified Petroleum Gas (LPG) and Compressed Natural Gas (CNG), is named consistently as a policy priority across advanced economies. The implementation of such strategies must act simultaneously on two fronts: prompting consumers to buy cars running on alternative fuels (AF) and increasing the number of refill stations offering such fuels.[1] Although the interdependence of these two goals has obvious implications for the effectiveness of alternative fuel adoption policies, the role of fuel availability in green cars demand is seldom considered.

This paper develops and estimates a joint model of demand for cars and supply of fuels. On the demand side, I model the consumer demand for cars with particular emphasis on the choice of the type of fuel the car runs on. On the supply side, filling stations must decide whether to install alternative fuel pumps on top of providing gasoline and diesel. The link between the two sides of the model is given by the fact that customers care about refilling costs. Hence, when choosing their car, they take into account the price and the density of stations offering the type of fuel utilized. At the same time, filling stations will only be willing to install AF pumps if there are enough customers driving cars powered by AF in the area. This unified framework allows for the joint analysis of the effect of different environmental policies. In a counterfactual exercise, I compare the effectiveness of subsidizing the cost of installing LPG and CNG pumps (supply push) to that of supporting the adoption of green cars (demand pull). I find evidences of the effectiveness of filling station subsidies on AF vehicles adoption.

The setting for this study is the Italian market, which is characterized by a high share of new LPG and CNG cars and a heterogeneous dislocation of filling stations among markets. I assemble a novel dataset which is uniquely suited to study the question, merging information from several sources. I collect data on car sale price, fuel type and other characteristics for newly purchased cars by private holders. I, then, combine them with information on location and range of fuels offered by the universe of filling stations active in 2012 in Italy. Moreover, I exploit differences in local legislation relative to traffic limitations for traditional fuel cars, reduced taxes for alternative fuel

[1] For example, in European Directive 2009/28/EC of the European Parliament and of the Council sets a market share target of 10% of renewable vehicles in transport fuels. See European Directive (2014) which "sets out minimum requirements for the building-up of AF infrastructure, including recharging points for electric vehicles and refueling points for natural gas (LNG and CNG) and hydrogen". In the USA, 1990 Clean Air Act, CAFE standards (2002) and Energy Independence and Security Act (EISA) of 2007.

vehicles and laws imposing filling stations the supply of at least one alternative fuel.

The empirical analysis consists of two steps. First, I set up a standard discrete choice demand model, assuming that car choice depends, among other things, on fuel costs and filling station density. I specify a nested logit, considering cars with the same fuel-type closer substitutes than other vehicles.

Next, I model the decision of gas stations to add an alternative fuel pump as an entry decision (in the spirit of Bresnahan and Reiss, 1991). and Berry and Waldfogel (1999). The number of alternative fuel retailers is the result of an entry game of complete information, where variable profits accrued to a firm depend on the estimates of the demand side of the model.

The main takeaway of the demand model is that consumers are sensitive to fuel availability and this effect is especially strong for AF. That is, demand pump density elasticity for green cars is 0.26 and 0.36 for LPG and CNG cars respectively. The elasticity to density of traditional fuel cars is only 0.13 for diesel and 0.04 for gasoline cars.

On the gas station side, estimation implies that the fixed cost of adding an LPG pump is €41,681 while adding a CNG pump is €163,388, an estimate that is consistent with values reported by experts of the sector.

Lastly, I use the demand and entry estimates to simulate the effects of two alternative policies designed to boost AF cars adoption: a 2,000€ rebate on the price of AF cars and a 50% subsidy to the installation of an AF pump. Subsidizing consumers would increase the share of LPG cars by 29.83% and CNG cars by 33.31%, leading to a 3.09% and 5.31% increase in the density of filling stations. Subsidizing gas stations would increase the availability of AF by 59.86% (LPG) and 65.67% (CNG): such a policy would increase the car share by 16.92% and 96.09% respectively for LPG and CNG. These results suggest that subsidizing fuel retailers to offer AF is an effective policy to indirectly increase AF vehicle sales. However, comparing the two policies results are mixed and should be evaluated at market level.

To my knowledge, this is the first paper to propose a full-fledged demand and supply model to study the incentives to alternative fuel adoption. Shriver (2015) considers a similar framework but with a more stylized demand model, where car price does not play a role. Furthermore, this is one of the first papers to consider fuel availability as a determinant for the demand of cars. Huse and Lucinda (2014) estimate a rich model for car demand, including fuel type among the relevant characteristics. However, they do not consider the role of fuel availability. The modeling choice of including fuel availability is supported by empirical evidence. Langer and McRae (2013) use real world driving data with traditional fuels to provide compelling evidence that this dimension plays a key role in fuel vehicle choice.

The policy question this paper addresses relates to the vast literature on government intervention to limit fossil fuel consumption and promote green fuels. For instance, there is growing literature that tries to identify to what extent consumers take into account future savings in fuel costs when buying fuel efficient cars.[2] Another strand in the literature examines the effect of standards (CAFE regulation in the US) on new car adoption (Goldberg, 1998 and Austin and Dinan, 2005) and used car adoption (Jacobsen, 2013). Closer to my research question, Beresteanu and Li (2011) investigate the effects of federal income tax incentives on the demand for hybrid vehicle.

The paper is organized as follows. Section 2 provided information on the green car market in Italy are and presents data sources. Section 3 and 4 discuss the model and the econometric specification. Section 5 shows and discusses estimation results. Section 6 presents policy counterfactuals, in particular a comparison between car price rebates and filling station subsidies. Section 7 concludes.

2 Data and background

2.1 Data

I combine data from multiple sources to construct two main databases used in the analysis. The first contains information on quantities, prices and characteristics of all the cars sold in Italy in 2012; the second includes details on location and fuel offer of Italian gas stations in the same year.

Automobile sales, prices and characteristics

I obtain car sales at municipality level from the vehicle registration database[3] (vehicle registration is mandatory in Italy). I focus on private purchases and drop corporate car purchases, this leaves 882,641 cars sold in 2012. Prices and other characteristics have been collected from industry publications [4]. The price information includes the list price and the registration tax (IPT), which vary at local level.[5] The other car characteristics I consider are: horse power, type of fuel, fuel

[2]see Allcott and Greenstone (2012) for a recent detailed review. More recently, Allcott and Wozny (2014) and Grigolon Reynaert and Verboven (2014).

[3]maintained by *Automobile Club d'Italia* ACI

[4]"*Quattroruote*" and "*Panoramauto*"

[5]In some Provinces the tax is reduced for AF cars.

consumption, trunk capacity and acceleration time to speed from 0 to 100km/h.
Since the databases report data at different levels of aggregation (sales data are not broken down by optionals), I match car sales with price and characteristics of the standard equipment.[6]

Gas stations

The location and characteristics of filling stations were provided by *prezzibenzina.it*, an Italian website which offers information about retail gasoline prices and location as posted by website visitors and verified by the staff. Since 2009, they cover over 90% of the Italian filling stations. For the 19,892 filling stations active in Italy in 2012, I observe the fuels they offer and their location, I use the date in which they entered the database as a proxy of the entry in the market. I cross check these data with the ones provided by *www.ecomotori.net*, which lists all the stations offering AF and those reported in the Italian Competition Authority Investigation on off-brand conventional fuels filling station (AGCM, 2013).
I aggregate data at market level, considering Labour Market Areas (LMAs) as a market.[7] LMAs are sub-regional geographical areas developed by the Italian National Institute of Statistics (Istat), through an allocation process based on the analysis of commuting patterns.[8] There are 611 distinct areas. They are designed to obtain meaningful comparable sub-regional labour market areas. However, they perfectly adapt to define fuel markets, given their functional definition based on commuting patterns.[9]

2.1.1 Summary statistics

Table 1 reports summary statistics on vehicle characteristics weighted by sales, reported by fuel. The level of observation is a variant, defined as the combination of make, model, body type (including doors) and engine displacement.[10] I observe sales in 611 labour market area each month in 2012. Such a disaggregation leads to many variant/market/month combination with no sales.

[6]Performance characteristics are the same for all the equipments since the engine is the same.
[7]Local labour systems – SLL in Italian.
[8]2011 LMAs are based on commuting data stemming from the 15th Population Census.
[9]LMAs are designed to respect only municipality administrative boundary constraints: 56 of them cut across regional boundaries and 185 span across different provinces. However, 85% of interprovincial provinces are characterized by a prevalent province in which are concentrated more than 80% of the observations. I computed variables which varies at local level as a weighted average. Looking at regional tax legislation, only 34 car models were subject to different legislations.
[10]An example of variant is Volkswagen Golf: I can distinguish among different frames (sedan, station wagon, cabrio and multispace), the engine size and the fuel (1.2 TSI, 1.4 TSI, 1.6 TSI, 1.6 bifuel, 1.6 TDI, 2.0 TDI, 2.0 TDI 4 motion and 2.0 GTD).

[Table 1 about here.]

Table 2 reports summary statistics of the variable used to compute variable profit, the expected variable profit and a binary variable indicating whether in that LMA the regional law regulates the opening of a new filling station imposing the supply of at least three fuels.

[Table 2 about here.]

2.2 Italian Green Cars and Alternative Fuels Markets

Alternative fuels (AF) include, among others, ethanol, biodiesel, compressed and liquified natural gas, electricity and hydrogen. I focus on Compressed Natural Gas (CNG), or methane, and on Liquefied Petroleum Gas (LPG), or autogas, which represent the bulk of the market in Italy. Italy represents a very interesting market, since the share of AF cars (Figure 1), as well as the number of filling stations offering AF, is increasing. Although AF are different in nature and in their environmental impact, most of them not only produce much less tailpipe pollution and CO_2 emissions, but they can also be significantly cheaper to run. The market share of these types of cars is historically higher in Italy than in the rest of Europe: 77% of CNG European cars and 26% of LPG ones are registered in Italy. Further, Italian industry sector accounts for excellence both in engine transformation and in storage and distribution. Finally, there has been a significant legislative activity both on the supply of AF, with the liberalization of the retail fuel market,[11] and on the green car market, which benefited from generous incentives in 2009[12] in the form of a scrappage scheme.

[Figure 1 about here.]

The left panel in Figure 1 shows the share of cars sold in Italy from 2002 to 2014 by fuel type. The share of AF cars (LPG and CNG) shows a positive trend, in particular after 2006. Looking

[11] With the constitutional act n.3 of October 18th, 2001. Fuels retailing is not considered a public service any more and jurisdiction in regulating filling stations entry is assigned to Regions.
Law 6 Agosto 2008 n.133 removed bureaucratic barriers to entry.
The most recent regulation of the sector is the decree "Urgent provisions for competition, development of infrastructure and competitiveness" GU n. 19, 24 April 2012. It further liberalizes the sector and provides for the obligation of a decree to be issued by the Ministry of the Interior to "modernize" and amend the regulations pertaining to self-service and natural gas multi-dispensers.

[12] Dl 10 febbraio 2009, n.5 "Misure urgenti a sostegno dei settori industriali in crisi" - GU n. 34 11 febbraio 2009. It introduced a scrappage scheme for Euro4 new cars (€1,500) for traditional fuels. This incentives could be combined with purchase incentive of at least €1,500 for a new car running on LPG, CNG, electricity or hydrogen.

at the right panel in Figure 1, which displays quantities, it is clear that the increase in the share of AF cars is due to both an increase of the total quantity sold in the market and to a decrease of new car registrations in the Italian market since 2007. The peak registered in 2009-2010 could be explained by the scrappage scheme mentioned above. The incentive, in fact, could be claimed for purchases up to the first quarter of 2010. Although the whole sector was subsidized, only the additional incentives dedicated to AF cars seem to affect the quantity of new cars and the effect on the LPG is much stronger than the one on the CNG. This evidence is particularly interesting in order to study the role of the diffusion of filling pumps. As a matter of fact, one possibility is that LPG cars were more reactive to price incentives since their filling stations density was higher.[13]
The drop in volumes for AF cars in 2011 can be linked to the scheme that likely caused intertemporal substitution of demand due to the widespread belief that the incentive was temporary. In order to better understand the role of fuel price in the choice of green cars, Figure 2 shows the fuel cost per 100 km for an average "compact" car. CNG is the cheapest fuel, while LPG is always cheaper than gasoline and sometimes very close to diesel cost. Moreover, gasoline and diesel prices show an increasing trend, wile the AF price trend is more stable. Notice that alternative fuels are subject to a different tax regime with respect to traditional fuel regime, which contributes to widen the differences in running cost.

[Figure 2 about here.]

Figure 3 shows the diffusion of alternative fuel cars over the country (considering only private owners). We can see that LPG cars are sold all over the country while CNG cars are particularly concentrated in some areas.

[Figure 3 about here.]

Fuel price differences do not seem to play a role in explaining this heterogeneity since alternative fuel prices are not dispersed (the LPG and CNG price in 2012 were respectively 0.83€/liter and 0.98€/kilogram with a standard deviation of 0.053 and 0.037).[14] Geographical differences play a stronger role in the heterogeneous development of AF networks. Namely, mountainous regions are not covered by the networks and South and Island never developed a CNG network. While in

[13] See Appendix A.

[14] LPG and CNG are measured respectively in liter and in kilogram. Therefore, it is not possible to compare them directly. However, CNG is usually cheaper per kilometer to run than LPG, as shown above.

Sardinia the lack of a local pipeline has not allowed the development of a local CNG network, in the rest of the South of Italy the network did not develop given the lack of local investments. In mountainous regions pipelines are less accessible and refiling the station through trucks is more costly. Further, the maps show the first evidence of the strong correlation between AF cars share and the pump density (the black dots are the alternative fuel pump stations operating in 2012), which is also confirmed in Figure 4, where scatterplots between the share of AF cars sold in 2012 and the AF filling station density are presented. It already shows the strongly significant positive correlation which will be further investigated in what follows.

[Figure 4 about here.]

3 Empirical Model

The empirical model describes consumer demand for cars and filling stations' choices of entry in the AF retail industry. The model is static and the timing is as follows. The period starts with a given stock of registered cars for each type of fuel in each market. Then, existing traditional fuel stations simultaneously decide whether to add alternative fuel pumps, given the expected local market demand of fuel and the number of competitors. The expected demand of fuel depends both on the stock of already circulating cars and on the number of expected newly registered cars. Lastly, a consumer decides whether to buy a car with a certain fuel, given the number of filling stations in the market at the time in which she undertakes the decision. Consumers behave myopically, that is, they do not form expectations on the evolution of the number of circulating cars and filling stations.[15]

I introduce the model starting from the last stage. Identification of both sides of the model is discussed in Section 4.

3.1 Demand

Demand is modeled as a standard discrete choice problem with differentiated products. I assume that the consumer maximizes a linear utility, taking into account the characteristics of the vehicles.

[15]This assumption is dictated by the fact that the model is static. Myopic behavior when purchasing durable goods that vary in energy costs have been firstly studied by Hausman (1979). Although the focus of this literature is the energy cost and not its availability, the absence of conclusive evidence suggests that this assumption could be considered realistic. For a detailed overview of the literature, see Busse et al (2010).

I consider $m = 1, ..., M$ local markets (LMA), each with $h = 1, ..., H$ households. For each market I observe the quantity of sold cars; product characteristics for a car model $j = 1, ..., J$, which install a specific fuel $f = 1, ..., F$, are the same across markets. I assume that in a given year households can choose to buy a vehicle among the set of cars available in the market, or not to buy a new car. The potential market is defined accounting for annual household's income and the average vehicle age. I implement a nested logit model where cars are nested according to the fuel they run on.[16] Products are grouped in $F + 1$ exhaustive and mutually exclusive nests. The utility of the outside good (not buying a car) is normalized to zero. I define the indirect utility of a consumer h in market m from buying a car model $j(f)$, as a function of product characteristics, fuel characteristics and utility parameters to be estimated

$$\begin{aligned} u_{hj(f)m} = \delta_{j(f)m} + \nu_{hj(f)m} = \\ =&\alpha p_{j(f)m} + x_{j(f)}\beta + n_{fm}\lambda + \xi_{j(f)m} + \zeta_{hfm} + (1-\sigma)\varepsilon_{hj(f)m}, \qquad (1) \\ &h = 1, \ldots, H_m,\ j = 1, \ldots, J,\ m = 1, \ldots, M, f = 1, \ldots, F. \end{aligned}$$

where $\delta_{j(f)m} = \alpha p_{j(f)} + x_{j(f)}\beta + n_{fm}\lambda_h + \xi_{j(f)m}$ is the mean utility; $p_{j(f)m}$ is the price of a car model installing fuel f, $j(f)$, in market m[17], $x_{j(f)}$ is a vector of observed car characteristics, n_{fm} is the number of filling stations offering the fuel compatible with the car $j(f)$, $\xi_{j(f)}$ represents unobserved car characteristics.

To capture the correlation in taste across cars with similar fuels, I nest cars by the type of fuel f they run on. The individual specific part of the utility given by car j in market m is $\nu_{hj(f)m} = \zeta_{hfm} + (1-\sigma)\varepsilon_{hj(f)m}$, where $\varepsilon_{hj(f)m}$ is an i.i.d. extreme value term and ζ_{hf} is common to all products in group f and follows distributional assumption of a nested logit which depends on σ (Cardell, 1997).

3.2 Entry

The entry model regards the choice of filling station selling traditional fuels to enter the alternative fuel market adding a pump for LPG or CNG. I model this choice as a game of complete

[16] Although alternative fuel cars are mostly bi-fuel, I assume the consumers who choose these type of vehicles are mainly interested in performance characteristic of the car when it runs with the alternative fuel, given the price gap between these fuels and gasoline (see Figure 2).

[17] Price is indexed by m because the presence of local taxes makes it market specific.

information in the spirit of Bresnahan and Reiss (1991). I consider the alternative fuel market as a homogeneous good industry[18] and assume that all the gas stations operating in 2012 are potential entrants in the alternative fuel market.[19] Post entry profits accruing to firm i from offering a type of fuel in market m take the following form:

$$\Pi_{im} = \underbrace{(p_{im} - c_i)l_i(p_{im}, p_{-im}, n_m)}_{VP_i(n_m)} - F_{im} \tag{2}$$

where p_{im} represents the price per liter (kilogram) at which the firm sells the fuel and c_i is the marginal cost. The residual demand faced by the filling station is denoted by l_i (since it measures the liters or kilograms sold) and depends on the price set by the firm, those chosen by its competitors and the number of firms in the market.

In order to enter the market firms must pay a fixed cost F_{im} (independent from the number of firms in the market) to cover installation of new infrastructure.

In order to identify the parameter of post-entry profits I make the further simplifying assumptions (Berry and Waldfogel, 1999):

- Within markets, firms have identical marginal and fixed costs.[20]
- Drivers split their fuel consumption equally across gas stations[21] in a given market so that demand for fuel faced by a generic station in market m is:

$$l(q(n_m)) = \frac{1}{n_m}[k_m(q(n_m) + Q_m)] \tag{3}$$

where k_m is the average fuel consumed by a car compatible with the fuel offered by the station and Q_m and $q(n_m)$ are, respectively, the stock of already circulating cars consuming the fuel sold by the station and the number of newly registered cars consuming the fuel. The latter, as illustrated in the demand model, will depend on the number of filling stations selling the fuel in the market.

[18] Alternative fuels are not differentiated in regular and premium fuel as traditional ones.

[19] Since early 2000 new LPG and CNG pumps opened in traditional fuel filling stations thanks to changes in safety legislation, D.M. 2002 June, 28th.

[20] Marginal costs are strongly related to international fuel prices and are set by large companies at national level. Fixed costs are mostly related with building costs and new infrastructures are built by specialized firms.

[21] This assumption is coherent with both Salop (1979) circle competition and with Cournot competition, which are the two main ways of modeling competition in this market.

Hence, I can rewrite profits as $\Pi_{im} = (p_m - c)l(q(n_m)) - F_m = vp_m(q(n_m)) - F_m$.

4 Identification and Estimation

4.1 Demand

In order to estimate the mean utility parameters in (1), α, β and λ, I follow Berry (1994). I obtain a linear estimating equation for the logarithm of the market share of car j relatively to the market share of the outside good:

$$\ln\left(\frac{s_{j(f)m}}{s_{0m}}\right) = \alpha p_{j(f)m} + x_{j(f)}\beta + n_{fm}\lambda + \sigma \ln s_{j(f)|fm} + \xi_{j(f)} \quad (4)$$

where $s_{j(f)|fm}$ is the market share of product $j(f)$ within the nest f and $p_{j(f)m}$ is the price of the model j in the market m. In the demand specification I include both physical characteristics (length) and performance characteristics (ratio of power over weight and the acceleration). The only time varying characteristic is the fuel cost for 100km computed as the product of time-invariant fuel efficiency of the car (kilometers per liter) and the price of the fuel the car runs on, which instead varies in time. I also include month, LMA and brand fixed effect as well as segment fixed effect.

I take into account the endogeneity of price and market share of product $j(f)$ within the group f. As it is standard in the literature (Berry et al., 1994), I use as instruments the sum of the characteristics of cars used in the regression produced by the same firm and produced by other firms.[22] Moreover, I include two shifters of alternative fuel vehicles demand driven by local legislation: a dummy variable equal to one if at least a municipality in the LMA in 2010 blocked circulation of vehicles but alternative fuel ones for at least one day[23] and a dummy variable equal to one if the Region provides exemption for the annual taxes only for alternative fuel cars. Given the timing of the model and the characteristics of the filling station entry decision (it takes more than one year to open a new filling station), I consider the density of filling stations as an exogenous variable. In

[22] Instead of fuel costs, fuel efficiency is used for computing the instruments, since it is constant across markets.

[23] The European Directive 2008/50/EC on ambient air quality was adopted by Italian legislation in 2010 (D.Lgs. 155/2010 and D.Lgs 250/2012). Regional government can decide policy to undertake in case of passing limit level of SO2, NO2, C6H6, CO, Pb and fine particles (PM10 e PM2.5). Fine particles are the more relevant for urban traffic and many municipalities adopted weekend traffic closures to face the problem. Alternative fuel vehicles, being significantly lower on particle emissions are often exempt by traffic block. In order to identify the municipality that adopted this regulation we refer to a list available at the national association of Italian municipality, ANCI $http://www.anci.it/index.cfm?layout=dettaglio\&IdSez=10325\&IdDett=22223$

Appendix C I perform check of the robustness of my results to this assumption.

4.2 Entry

Given the assumption made in section 3.2, we will observe n_m such that

$$\Pi_m(q(n_m)) > 0 \text{ and } \Pi_m(q(n_m+1)) < 0 \tag{5}$$

I exploit several data sources to quantify the variable profit components so as to treat them as data. I will instead assume that fixed entry costs are not observed.

I use data from the ACI on the stock of existing cars by fuel in each market (Q_m in equation (3)) and information provided by the Ministry of Economic Development on average LPG and CNG consumption(k_m). Mark ups $(p-c)$ are considered constant at national level and are chosen according to provisional profit and loss accounts available on the Internet and confirmed by pump producer (toil.spa) and by interviewed pumps owners. Lastly, I compute the quantity of new cars $(q(n_m))$ given the functional form specified in the demand model.

I then assume that the logarithm of the fixed cost of entry in market m is:

$$ln(F_m) = \gamma W_m + \omega\nu_m \tag{6}$$

where γ and ω are the parameters we would like to estimate and ν_m is a standard normal. W_m is a vector of market specific observable cost shifters. Namely, I include cadestral value of the real estate and dummies which identify the presence of a regional law imposing the supply of one alternative fuel and geographical dummies. Equation (6) implies that n_m entrants in market m are consistent with the following inequalities.

$$\frac{ln(\widehat{vp_m}(n_m+1)) - \gamma W_m}{\omega} \leq \nu_m \leq \frac{ln(\widehat{vp_m}(n_m)) - \gamma W_m}{\omega}$$

where $\widehat{vp_m}(n_m)$ are the variable profits quantified using data sources mentioned above.

The distributional assumption on ν_m allows me to write the following likelihood for the event that n gas station decide to offer LPG in the market m.

$$\mathcal{L}(\theta) = \sum ln \left(\Phi \left(\frac{ln(\widehat{vp_m}(n_m)) - \gamma W_m}{\omega} \right) - \Phi \left(\frac{ln(\widehat{vp_m}(n+1)) - \gamma W_m}{\omega} \right) \right) \tag{7}$$

The parameters of fixed cost function, γ, are retrieved as those that maximize the likelihood.

4.3 Equilibrium

The equilibrium of the model is given by n^* and q^* that satisfy equation (5), given demand and entry parameters identified in equations (4) and (7). Following Breshnan and Reiss (1991), modeling the number of entrants, instead of identities, requires for uniqueness of equilibrium that profit is strictly decreasing in the number of entrants (that is, $\frac{\partial \Pi(n_f)}{\partial n_f} < 0$). However, the number of active AF stations enters nonlinearly in the profit function since $q(n_m)$ is a non linear function of n.[24] Then, this condition is not verified for any positive n.[25] Therefore, the model has multiple equilibria. However, the profit function is decreasing in n over the support $[0,\bar{n}]$, where $\bar{n}$ is the maximum number of stations observed in any market in the data. Therefore, I can solve the multiplicity problem by selecting the only equilibrium where the resulting number of firms lies in the support observed in the data.

5 Empirical Results

5.1 Demand

In Table 3 I report the coefficients estimated using a standard OLS logit regression, an IV logit and IV nested logit.

[Table 3 about here.]

Market size is given by the total number taxpayers with annual income higher than 10,000 euro living in the LMA, scaled to accommodate for the fact that cars are durable goods.[26] I also tried different specifications, assuming households consider whether to buy a car every 5 or 6 years and

[24] See Appendix 2 for further details.

[25] for some n, $q(n+1) >> q(n)$ to the point that $q(n+1)/(n+1) > Q(n)/n$

[26] I assume that taxpayers consider to buy a new car every 4 years, given evidence on Italian car market (ACI statistics, 2014).

results are in line with the ones presented.

Price has a significant and negative impact on consumers' mean utility. In particular, the implied average own-price elasticity is -3.48 in the nested logit, which is in line with other estimates of the European cars' market (Goldberg and Verboven, 2001.

The physical dimensions of the car have a positive and significant effect on the mean utility, while the performance characteristics have a less clear effect, acceleration time is negative and significant while power/weight is more sensitive to model identification. The estimate of the fuel costs parameter is negative and significant. However, it is sensitive to model specification, suggesting that one possible rationalization of this puzzling result is that consumers are more sensitive to the reduction of costs related to deviations from their optimal route than fuel cost savings.

This is further confirmed by the analysis of the coefficients on filling stations availability. I include pump density interacted with fuel dummies in order to allow for a different relationship between fuel availability and cars demand, while keeping mean utility linear. This specification can accommodate S-shaped relationship between fuel availability and cars demand, given that the density of filling station is homogeneous among markets. All density parameters are positive and significant in the three specifications (the additional effect of diesel is negative but the overall effect is positive). However, increasing density of LPG and CNG has a positive effect, greater in magnitude with respect to the traditional fuels one. In the nested model, the effect of rising by 1% the density of filling stations for AF increases demand for green cars by, respectively, 0.78% for LPG cars and 0.84% for CNG cars, while the impact of the same variation in the density of traditional fuels on diesel and gasoline cars is respectively 0.36 % and 0.5%.

The nesting parameter is significantly different from zero and satisfies the restrictions for consistency with random utility maximization in a nested logit ($0 < \sigma < 1$). The results imply that consumer preferences are more strongly correlated across vehicles with the same fuel-type. However, the small nesting parameter, equal to 0.24, still allows for substitution patterns across fuels.

Table 4 lists the average own and cross-price elasticities of demand. Note that along the main diagonal are reported the average price elasticities of demand for the same fuel, which are higher than cross fuel elasticity. That is, consumers perceive cars with the same fuel closer substitutes than cars with different fuels, which is particularly true for AF cars (the elasticities within nests are higher for AF cars).

[Table 4 about here.]

5.2 Entry

Table 5 reports estimates of the parameters of an ordered probit obtained by exploiting post-entry information on variable profit, holding demand estimates fixed.

The constant term parameters represent the logarithm of the mean of the distribution of the fixed costs and ω is the estimated standard error of the logarithm of fixed costs. Therefore, the implied mean fixed cost is $40,028$€for LPG and 143,389, which is about half the actual fixed cost reported by experts of the sector for adding a new pump offering LPG or CNG.[27] The estimated standard errors ω are equal to 0.72 (LPG) and 0.61 (CNG), which implies a fixed cost variance depending on market characteristics almost three-quarter of the mean fixed cost. Geographical location does not to play a crucial role in the determination of fixed costs.

[Table 5 about here.]

6 Policy experiments

6.1 Car price rebates vs. filling station subsidies

I use estimated model to compute the effect of different policy incentives to adopt alternative fuel vehicles. I compare the effectiveness of supporting the adoption of green cars by offering car price rebates (demand pull) to that of subsidizing the cost of installing alternative fuel pumps (supply push).

For the demand incentive, I consider the effect of a 2,000€ reduction on the sticker price of alternative fuel cars. The price rebate is in line with the 2009 Italian rebate program and other European scrapping schemes (Huse and Lucinda(2014) and Grigolon, Leheyda and Verboven(2015)).[28] I distinguish between a "direct effect" defined as the market share of cars running on a particular fuel, keeping fixed the number of filling stations, and an "overall effect", which factors that the increase in market share of AF cars affects the entry choice of filling stations leading to a new equilibrium. I compare these outcomes with those deriving from a 50% reduction in fixed costs when adding an alternative fuel pump. The size of this entry subsidy is calibrated so that it mirrors regional

[27]The figure was reported by an expert of Kalorgas s.p.a.

[28]In Italy the scrappage scheme involved rebates for purchase of both traditional and alternative fuel cars, the latter, however, were more generous. 2,000€ is the approximate difference in the rebates for the two type of cars.

subsidies implemented in 2014-2015 in some regions of Italy.[29]

In this exercise, I compute the new equilibrium after I reduce by 50% the fixed cost parameter γ_0. The new equilibrium number of AF filling stations is the smallest integer value which satisfies condition (5), given the quantity of cars sold in the baseline equilibrium. This gives me the "direct effect". I determine the "overall effects" by computing the estimated quantity of alternative fuel cars and the number of filling stations which satisfy the entry condition (5) for $\Pi(\widehat{q(n)})$, where $\widehat{\Pi}(n)$ is derived following the procedure described in section 4.2.

Computing the "overall effects" of both policies allows me to compare their impact on the composition of new sales by fuel type and alternative fuel pump densities. All results are reported as percentage deviation from the baseline equilibrium.

When accounting for effect of policies on CO_2 emissions and particulate pollutants, it is in principle relevant to distinguish between consumers scrapping an existing car (presumably with higher emissions) and consumers buying a new car and, hence, increasing the stock of circulating cars. In this case, even if the new car runs on green fuels, its purchase would result in an increase of the emitted CO2. However, my framework does not allow for such distinction, since I do not model scrappage decision. Hence, I simply compare the effect of the policies on the CO_2 emitted by the new cars sold in 2012, disregarding emissions from cars sold pre-2012.

Table 6 reports the average percentage difference between the estimated market shares under the baseline model and price reduction of each alternative fuel type car by $2,000$€.

[Table 6 about here.]

The "direct effect" of the policy implies an increase in LPG and CNG market share respectively by 23.84% and 15.39%. The effect of the policy on traditional fuel type cars market share is relatively small and mirrors the substitution patterns showed in Table 4. That is, the extra market share of AF cars mainly comes from the outside good. However, looking at the "overall effect", not only the AF market shares increase, but also consumers substitute more between traditional and AF vehicles. We observe an overall effect of LPG vehicles price rebate on LPG vehicles market share by 29.83%, the reduction of traditional fuels market share by 2.16% each and the increase of LPG pump density by 3.09%. In the case of CNG vehicles price rebate, the effect is even stronger: CNG

[29] In 2015 Liguria subsidizes builders of alternative fuel pumps with free grants covering half of the building costs. Between 2014 and 2015 Region Piemonte financed 30 CNG filling stations with 150,000€ and 3 with 80,000€. In 2014 Region Lombardia provided subsides equal to 50% of the fixed costs.

vehicles market share increases by 33.31%, the reduction of traditional fuel vehicles is about 7% each and CNG filling station density increases by 5.31%. I also report the effect of the policies in the markets in which the LPG (CNG) market share variation was equal respectively to the 5^{th} and 95^{th} percentile. The results show the complexity of the effect pattern at market level. Namely, substitution patterns are not stronger in case of stronger market share effects.

Table 7 reports the variation in the estimated number of pumps per square kilometers under the baseline situation and after a decrease of the fixed costs of installing a pump by 50%.

[Table 7 about here.]

Under this scenario, the LPG and CNG filling station density rises by, respectively, 59.86% and 65.67%. Looking at the difference between "direct" and "overall" effects of the policy, the demand pushes an extra 10% and 30% increase in filling station density. The overall effect of the policy on the market share is stronger in case of CNG and it is due to the higher elasticity of CNG vehicles pump density.

The variability of the results suggests an heterogeneous effect of policies across markets. I report in Figure 5 and 6 the total average effects of the two counterfactuals on market share and pump density in each LMA. The maps show that price subsidies have a more homogeneous effect all over the country, particularly in case of LPG, while the subsidies to filling stations are more concentrated.

[Figure 5 about here.]

[Figure 6 about here.]

Since the cost of the two policies differ, I perform a back-of-envelope calculation to compute euro spent per CO_2 emission reduction to compare the effectiveness of the two policies. Given the price rebate "direct effect", there would be about 150 thousand cars eligible for the consumer subsidy, with a consequent cost of the price rebate program of about 300 million euros in government revenue. The filling station subsidy applies to more than 5000 LPG pumps and 2000 CNG pumps. Subsidizing all of them would cost about 450 million euros.[30]. However, difference in cost expenditures varies across market,as shown in Figure7.

[30]Here I consider average fixed cost reported by industry experts: about 100,000€for LPG filling stations and 200,000€for CNG. In the policy simulation I consider all filling stations new entrants. Hence, the cost is computed as if all of them had to be subsidized.

[Figure 7 about here.]

The histograms show the distribution across markets of the difference in costs between the vehicle price rebates and the filling station subsidy distinguishing between LPG and CNG policy targets. That is, when the cost difference is higher than zero, the vehicle price rebates are more costly while the contrary is true when the cost difference is smaller than zero. In most of the markets (55% for LPG and 65% for CNG) the cost difference is around zero. The higher cost of the filling station subsidy policy is strongly correlated to the stock of existing AF cars. Given equations (2) and (3), stock of cars contributes to the determine the level of Π and so the number of filling stations entering the market (and the number of subsidies) increase.[31]

Finally, I calculate whether the policies induce a reduction in CO_2 emissions per kilometer, since the LPG and CNG cars produce respectively 2.5% and 9.3% less CO_2 emissions with respect to gasoline cars.[32] Both policies imply, on average, a 1% CO_2 reduction per car, showing again high variability among markets. In order to compare the cost effectiveness of the policy in terms of reduction of CO_2 grams per circulating cars, I divide the total cost of the policy in the market by the CO_2 reduction implied by the market shares under the two counterfactuals.

[Figure 8 about here.]

Results are shown in Figure 8. The bulk of the observations is concentrated around zero. The higher cost effectiveness of price rebate is due to the substitution between traditional fuel vehicles and AF ones, which is smaller in case of filling station subsidies.[33]

Although consumer rebates are more effective in terms of CO_2 per car reduction, they do not indirectly support the entry of filling stations. Therefore, the effect of the policy lasts for the duration of the subsidy. On the other side, the effect of a filling station subsidy on AF market shares would continue in the following years since filling stations would remain in the market. Moreover, consider that 2009 price rebates were introduced as an economic stimulus to increase market demand

[31] These are also the markets in which the number of installed pumps is higher.

[32] CO_2 emissions are computed as mean weighted by sales of declared CO_2 emissions per kilometers as reported in 2012 price list. If we consider Well to Wheels (WtW) evaluation of CO_2 emissions of vehicle use as reported by the European Energy Agency (TERM 2012: transport indicators tracking progress towards environmental targets in Europe), emission difference would widen up to 10-22% for LPG and 24% for CNG.

[33] As shown in Section2.2, between 2006 and 2014, Italian car market faced a strong decline in sales which was, in 2012, equal to 20% with respect to the corresponding month of the previous year. Therefore, the outside good share in these years are increasing and it contributes to explain the high substitution between outside good and AF.

for the car sector during the economic crisis, targeting the support to low-emissions vehicles. The results of the price rebate counterfactual mirrors what happened in that year, the LPG market share “direct” effect was stronger than CNG. However, the filling station subsidy counterfactuals show to be more effective in supporting indirectly market demand.

The main takeaway of this comparison is twofold: first, the effectiveness of the policies should be evaluated at the local level. Second, filling station subsidies are cost effective policies which could be expected to be more persistent.

6.2 Filling station standards

In the second counterfactual, I simulate the effect of the European Directive No.94(2014) that “sets out minimum requirements for the building-up of alternative fuels infrastructure”. Since the Directive does not quantify the minimum requirement, in my exercise I assume it mandates to bring all markets at least to the pre-reform average in terms of AF pump density. Results are reported in Table 7

[Table 8 about here.]

The impact of the increase of filling station density at the average level on alternative fuel market shares is smaller than in previous policy analyzed. In fact, the average density level is low and reaching that target does not represent a strong policy intervention. To provide an “upper bound” to this type of “mandate density policies” I calculated what would be the effect of bringing the density of AF pumps to the same level of the regular fuels. In this case, the pump density variation of CNG is much bigger than the LPG one (LPG network is three times bigger than CNG one). CNG market share would also react more since its pump density elasticity is high. The results confirm that pump density increase is effective in stimulating demand only if it means a large increase in the number of pumps. In this extreme example the large majority of newly sold cars would be on a green fuel.

[Figure 9 about here.]

Differently from before, market share variations are stronger where pre-existing markets where weak. These results are important because they highlight the incidence of the regulation shifts with market characteristics.

7 Conclusion

Assembling a rich database on cars sold and filling station locations in 2012, I document the importance of fuel availability in the choice of adopting AF vehicles. I find that pump density elasticity is over twice as high for AF vehicles than for traditional fuel ones. I develop and estimate a joint model of demand for cars and entry of AF fuels station to compare different policies to foster green car adoption. First, I compare the effect of a price-subsidy on the adoption of alternative fuel cars with a fixed cost reduction for new pumps supplying AF. Then, I consider the effect of increasing filling station density to different standards.

On the one hand, I find that price rebates is an effective policy to foster the use of AF cars including large market share variation is above 25%. However, its indirect effect on AF pump density (3.09% for LPG and 5.31 for CNG) suggest that the effect would disappear once the subsidy expired. On the other hand, subsidy to AF filling stations show strong effects on both size of the markets. The effect on the supply side implies that its impact would be more persistent the consumer subsidies. Both of the policy imply a change in market composition such that CO_2 produced per car is reduced by 1%. However, relevant market heterogeneity suggests that policy comparisons should be performed at a more local level taking into account the AF targeted for the policy. Finally, I find that fixing a standard density for AF filling stations has widely different effects depending on the definition of what "minimum requirements" means. This paper is the first to compare the effect of different policies targeted to the two sides of the market, finding evidences of the importance of modeling the two markets together in order to compare the overall effects of the subsidies. My analysis has, however, some limitations. First of all, I model consumers and filling stations in a one-shot game while the durability of cars and, even more so, infrastructures, would suggest that dynamic effects may be important. Moreover, I do not consider cars manufacturers decisions, taking vehicle choice set exogenous. I focus only on sales of new vehicles and I do not consider the effect of the policy on "after-market" gasoline engine conversion to AF ones or on car replacement. Finally, the effects on CO_2 emissions are computed ignoring possible effects on driving behavior. Each of these issues could be material for future works.

References

[1] AGCM (2013). *Impianti di distribuzione carburanti indipendenti.* (IC44)

[2] Allcott, H., Greenstone, M.(2012). Is There an Energy Efficiency Gap? *The Journal of Economic Perspectives*. 26(1), 3-28.

[3] Allcott, H., Wozny N. (2014). Gasoline Prices, Fuel Economy, and the Energy Paradox. *Review of Economics and Statistics*, 96(10), 779-795.

[4] Anderson, S.T., Parry, I. W. H., Sallee, J.M., Fischer, C. (2011). Automobile Fuel Economy Standards: Impacts, Efficiency, and Alternatives. *Review of Environmental Economics and Policy*, 5(1), 89–108.

[5] Anderson, S T., Sallee. J.M. (2011) Using Loopholes to Reveal the Marginal Cost of Regulation: The Case of Fuel-Economy Standards. *American Economic Review*, 101(4) 1375-1409.

[6] Austin, D., Dinan, T. (2005). Clearing the Air: The Costs and Consequences of Higher CAFE Standards and Increased Gasoline Taxes. *Journal of Environmental Economics and Management*, 50(3), 562-582.

[7] Bento, A., Goulder, L., Jacobsen, M., von Haefen, R. (2009) Distributional and Efficiency Impact of Increased U.S. Gasoline Taxes. *American Economic Review*, 99(3), 667-699.

[8] Berry, S. (1994) Estimating Discrete-Choice Models of Product Differentiation. *The RAND Journal of Economics*. 25 (2), 242–262.

[9] Berry,S., Levinsohn, J., Pakes,A. (1995). Automobile Prices in Market Equilibrium. *Econometrica*, 63(4), 841-890.

[10] Berry, S., Waldfogel J. (1999a) Free Entry and Social Inefficiency in Radio Broadcasting. *RAND Journal of Economics*, 30(3):397–420.

[11] Beresteanu, A., Li, S. (2011) Gasoline Prices, Government Support, and the Demand for Hybrid Vehicles in the United States. *International Economic Review* 52(1) : 161-182.

[12] Bresnahan, T. F., Reiss P. C.(1991). Entry and Competition in Concentrated Markets. *Journal of Political Economy*, 99(51):977–1009.

[13] Busse, M.R., Knittel C.R., Zettelmeyer, F. (2010) Are consumers myopic? Evidence from New and Used Car Purchases. *American Economic Review*, 103(1): 220-256.

[14] Cardell, N.S(1997) Variance Components Structures for the Extreme-Value and Logistic Distributions with Application to Models of Heterogeneity. *Econometric Theory*, 13, 185- 213.

[15] Directive(EU) No.94/2014 of the European Parliament and of the Council of 22 October 2014 on the deployment of alternative fuels infrastructure.

[16] Goldberg, P. K., (1998) The Effects of the Corporate Average Fuel Efficiency Standards in the US, *Journal of Industrial Economics*, 46 (1), 33.

[17] Goldberg, P. K., Verboven F. (2001) The Evolution of Price Dispersion in the European Car Market. *Review of Economic Studies*. 68(4), 811–48.

[18] Greene, D. L. (1996) Survey Evidence on the Importance of Fuel Availability to the Choice of Alternative Fuels and Vehicles. *Energy Studies Review*, 8, 215-231.

[19] Greene, D., Patterson, P., Singh, M., Li, J. (2005). Feebates, Rebates and Gas-Guzzles Taxes: A Study of Incentives for Increased Fuel Economy. *Energy Policy*, 33(6), 757-775.

[20] Grigolon, L., Leheyda,N. & Verboven, F. (2015) Scrapping Schemes in the Financial Crisis – Evidence from Europe. *International Journal of Industrial Organization*, forthcoming.

[21] Grigolon, L., Reynaert, M., & Verboven, F. (2014). Consumer Valuation of Fuel Costs and the Effectiveness of Tax Policy: Evidence from the European car market. *Mimeo*

[22] Jacobsen, M. (2013) Evaluating U.S. Fuel Economy Standards in a Model with Producer and Household Heterogeneity. *American Economic Journal: Economic Policy*, 5(2), 148-187.

[23] Hausman, J. A. (1979). Individual Discount Rates and the Purchase and Utilization of Energy-Using Durables. *The Bell Journal of Economics*, 33-54.

[24] Huse, C., Lucinda, C. (2014) The Market Impact and the Cost of Environmental Policy: Evidence from the Swedish Green Car Rebate. *Economic Journal*, 124: F393–F419.

[25] Katz, M. L., Shapiro, C. (1985). Network Externalities, Competition, and Compatibility. *American Economic Review*, 8(2):93–115.

[26] Klier,T. and Linn, J. (2010). The Price of Gasoline and New Vehicle Fuel Economy: Evidence from Monthly Sales Data. *American Economic Journal: Economic Policy*, 2(3), 134-153.

[27] Langer, A., McRae S. (2013) Fueling Alternatives: Evidence from Naturalistic Driving Data. Working paper.

[28] Mc Fadden D.(1973) Conditional Logit Analysis of Qualitative Choice Behavior. in *Frontier of Econometrics*, ed. by P. Zarembka. New York: Academic Press.

[29] Shriver, S. (2015) Network Effects in Alternative Fuel Adoption: Empirical Analysis of the Market for Ethanol. *Marketing Science*, 34(1) 78-97.

[30] Verboven, F. (1996) International Price Discrimination in the European Car Market. *RAND Journal of Economics*, 27(2): 240-268.

Table 1: Summary statistics - Demand

VARIABLES	LPG	CNG	DIESEL	GASOLINE
price (thousands of €)	16.17	18.49	23.61	14.98
	(4.11)	(5.93)	(9.04)	(6.11)
power/weight (kw/kg)	0.06	0.05	0.06	0.06
	(0.01)	(0.01)	(0.01)	(0.01)
fuel cost (€/100 km)	6.08	4.29	8.33	9.96
	(0.86)	(0.85)	(1.65)	(1.66)
acceleration (seconds)	12.99	13.40	11.99	12.98
	(1.60)	(1.85)	(2.13)	(2.14)
truk (l)	285.74	256.06	374.38	275.98
	(80.75)	(175.43)	(126.18)	(98.89)
(pump/kmsq)*100	1.90	0.77	11.86	12.50
	(1.56)	(0.78)	(10.87)	(11.12)
CO2 emissions (g/km)	122.39	116.67	125.91	127.46
	(16.98)	(14.48)	(24.67)	(20.89)
N. of observations	41091	12826	216326	131046
N. of variants	90	21	647	672

Note: The table reports summary statistics of car characteristics sold in 2012 (standard errors in brackets). The table presents vehicle characteristics that are sales weighted over the 611 observed LMA in 2012 by fuel type. Price includes local taxes.

Table 2: Summary statistics - Entry

VARIABLES	LPG	CNG
fuel per car	1313.44	1492.57
	(790.82)	(371.98)
land value	2.72	2.72
	(0.00)	(0.00)
pumps	5.03	1.65
	(8.72)	(3.03)
stock cars	2931.70	1202.33
	(8645.44)	(2883.76)
Observations	611	572

Note: The table reports summary statistics on filling stations' variable profits at market level.

Table 3: Demand Results

VARIABLES	(1) Logit Demand	(2) IV Logit Demand	(3) IV Nested Logit
price	-0.01	-0.21	-0.14
	(0.0004)	(0.0183)	(0.0141)
sigma			0.24
			(0.009)
log(power/weight)	-0.52	0.01	-0.13
	(0.017)	(0.053)	(0.040)
log(euro/100km)	-0.30	-0.56	-0.54
	(0.007)	(0.026)	(0.020)
log(acceleration)	-0.07	-1.94	-1.34
	(0.021)	(0.176)	(0.134)
log(length)	0.10	0.19	0.14
	(0.008)	(0.013)	(0.010)
lpg*pump/kmsq	0.05	0.05	0.10
	(0.002)	(0.003)	(0.003)
cng*pump/kmsq	0.30	0.39	0.34
	(0.006)	(0.011)	(0.008)
diesel*pump/kmsq	-0.00	0.01	0.01
	(0.000)	(0.001)	(0.001)
gasoline*pump/kmsq	0.00	-0.01	0.00
	(0.000)	(0.001)	(0.001)
fuelFE	YES	YES	YES
marketFE	YES	YES	YES
monthFE	YES	YES	YES
segmentFE	YES	YES	YES
modelFE	YES	YES	YES
R^2	0.80	0.69	0.83
mean elasticity	0.29	-4.20	-3.48

Note: In column (2) price is instrumented while in column(3) price and within group market share are instrumented. F-statistics for the first-stage regressions are 8245 and 1892. The instrumental variables are the sum of the characteristics of cars used in the regression produced by the same firm and produced by other firms, dummy variables equal to one in presence of city laws which favor the circulation of AFl car or regional laws that discount annual taxes for AF cars. Standard errors in brackets.

Table 4: Substitution pattern

fuel group	average own elasticity	average cross elasticity wrt car with fuel: lpg	cng	diesel	gasoline
lpg	-2.774	0.094	0.004	0.008	0.004
cng	-3.056	0.003	0.089	0.004	0.003
diesel	-4.156	0.006	0.005	0.095	0.008
gasoline	-2.626	0.005	0.005	0.012	0.074

Note: The table lists the average own and cross-price elasticities of demand for each nest.
Average price elasticity is different for each fuel. The pattern of the cross-price elasticities reflects model assumptions: the average cross-price elasticities between same-fuel cars are higher than the cross-price elasticities between cars with different fuels. This pattern is much more pronounced for alternative fuel cars.

Table 5: Entry Results

VARIABLES	LPG	CNG
constant	10.64	12.00
	(0.23)	(0.23)
ln(land value)	0.06	0.01
	(0.02)	(0.02)
mandatoryAF	0.14	-0.20
	(0.07)	(0.09)
north-east	-0.08	0.05
	(0.11)	(0.11)
center	-0.08	0.37
	(0.11)	(0.11)
south	-0.30	0.21
	(0.10)	(0.11)
islands	-0.47	-0.16
	(0.12)	(0.17)
ω	0.72	0.61
	(0.02)	(0.03)
Observations	611	572
Implied fixed costs	41681	163389

Note: The table reports the coefficients of the ordered probit estimated through maximum likelihood. The main coefficient of interest is the constant. The implied mean fixed cost are reported in the bottom line. I am not reporting the marginal effects, since I am only interested in coefficients' signs.

Table 6: AF car price rebate counterfactual.

(a) LPG

	Avg (% Δ)	5^{th} LPG percentile (%Δ)	95^{th} LPG percentile (% Δ)
		Direct effect	
LPG	**23.84**	**22.25**	**29.22**
CNG	-1.02	-3.55	-1.42
Diesel	-1.02	-3.55	-1.42
Gasoline	-1.02	-3.55	-1.42
		Overall effect	
LPG	**29.83**	**24.10**	**37.12**
CNG	-2.01	-5.33	-3.63
Diesel	-2.16	-5.33	-3.63
Gasoline	-2.16	-5.33	-3.63
LPG pump density	3.09	0.00	20.78

(b) CNG

	Avg (% Δ)	5^{th} CNG percentile (%Δ)	95^{th} CNG percentile (% Δ)
		Direct effect	
LPG	-0.82	0.00	-0.85
CNG	**15.39**	**0.00**	**29.96**
Diesel	-0.82	0.00	-0.85
Gasoline	-0.82	0.00	-0.85
		Overall effect	
LPG	-6.32	0.00	-3.48
CNG	**33.31**	**0.00**	**50.12**
Diesel	-7.23	-1.11	-4.64
Gasoline	-6.09	-0.64	-3.48
CNG pump density	5.31	0.00	67.28

Note: The tables report the effects of 2,000€ price reduction of LPG (panel (a)) and CNG (panel(b)) cars considered one per time. The top panels reports the direct effect of this policy on the market shares, while the bottom panels report the total effect of this policy on both market share and filling station density. The first column refers to the average variation of market share and pump density. The second column and third column report the effect of the policy in the market in which the LPG (CNG) market share variation was equal respectively to the 5^th and 95^th percentile.
Results are average from 100 simulations of the model.

Table 7: Subsidy to AF gas station counterfactual.

(a) LPG

	Avg (% Δ)	5^{th} density percentile (%Δ)	95^{th} density percentile (% Δ)
	Direct effect		
LPG pump density	47.04	0.00	114.83
	Overall effect		
LPG	**16.92**	**1.21**	**13.14**
CNG	-1.10	-0.06	-0.59
Diesel	-1.12	-0.06	-0.59
Gasoline	-1.12	-0.06	-0.59
LPG pump density	59.86	0.00	153.42

(b) CNG

	Avg (% Δ)	5^{th} density percentile (%Δ)	95^{th} density percentile (% Δ)
	Direct effect		
CNG pump density	34.88	0.00	119.29
	Overall effect		
LPG	-4.06	0.00	-18.99
CNG	**96.09**	**0.00**	**560.08**
Diesel	-4.06	0.00	-18.99
Gasoline	-4.06	0.00	-18.99
CNG pump density	65.67	0.00	211.54

Note: The table reports the effects of a 50% reduction of the fixed costs of entry in the LPG market. The top panel reports the direct effect of this policy on the filling station density, while the bottom panel reports the total effect of this policy on both market share and filling station density. The second column and third column report the effect of the policy in the market in which the LPG (CNG) pump density variation was equal respectively to the 5^th and 95^th percentile.
Results are average from 100 simulations of the model.

Table 8: Setting filling station standard.

	(a) Average AF pump density Avg Δ (%)	(b) Gasoline pump density Avg Δ (%)
LPG	2.41	29.78
CNG	0.77	642.61
Diesel	-0.12	-18.75
Gasoline	-0.12	-18.75

Note: Column(a) reports the variation in market composition implied by increasing the pump density in markets where it is lower than the average level at the mean pump density. Column(b) reports the variation in market composition implied by the increasing filling station densities at the gasoline one.
Results are average from 100 simulations of the model.

Figure 1: Vehicles per type of fuels. Italy 2002-2014

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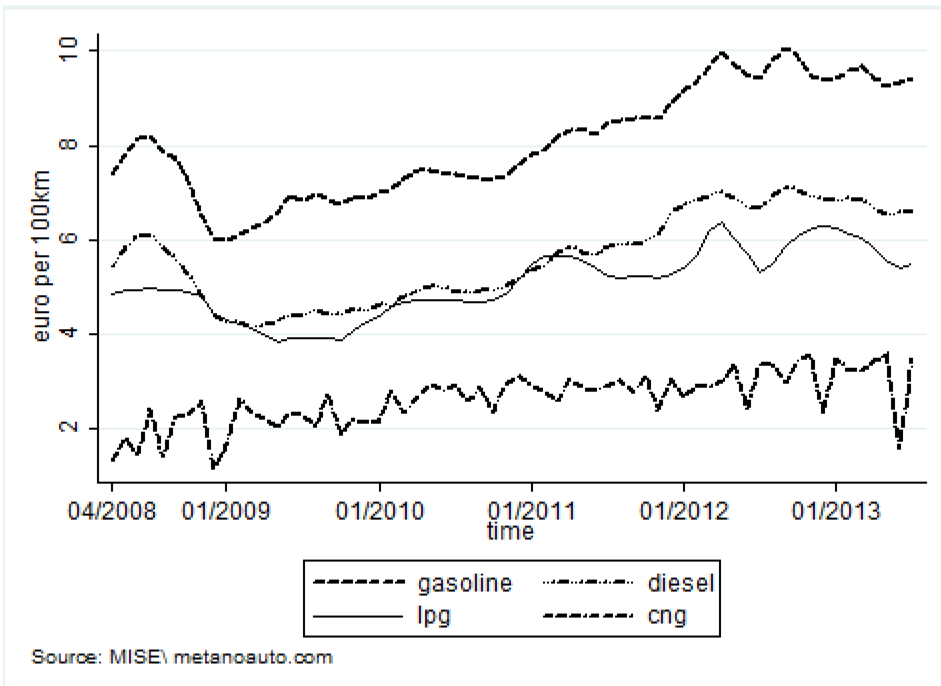
Note: The figure shows the market trend by fuel in Italy from 2002 to 2014.
The left panel plots the share of cars by fuel type.
The right panel plots the quantity of cars in levels.

Figure 2: Fuel price per 100 km



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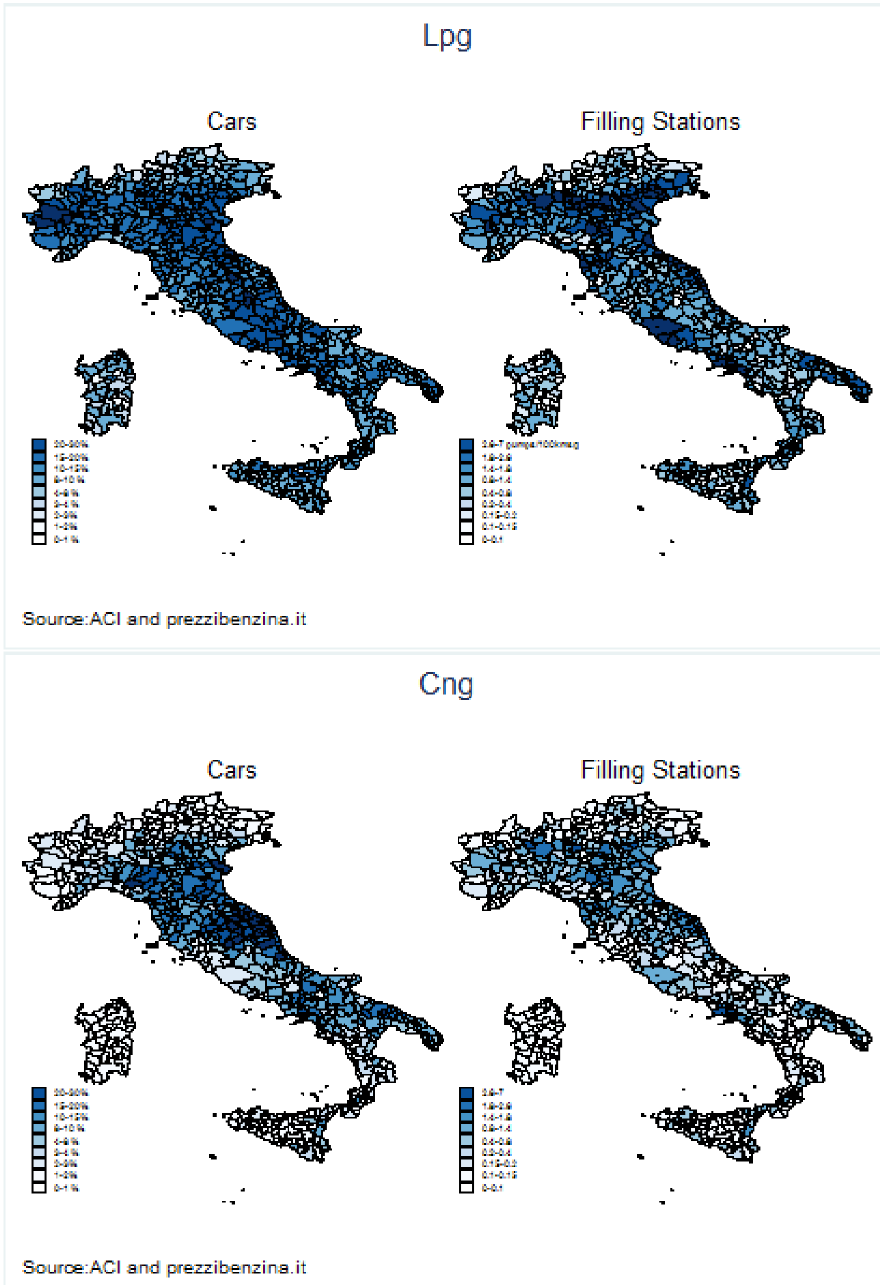
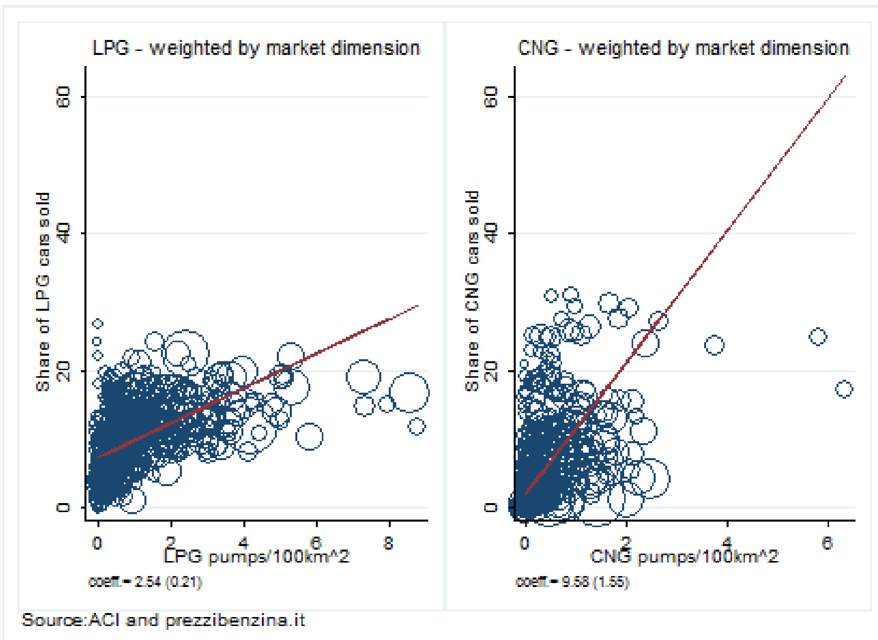
Note: The figure plots the fuel cost for running 100km from 2008 until 2013. Fuel costs are computed using the average fuel efficiency for "compact" cars (as reported in the specialized magazine "Quattroruote" September 2012). Fuel prices cannot be compared: CNG is not sold in liters but in kilograms and fuel efficiency varies per fuel. Gasoline and diesel price often move together and diesel cars are more than 30% cheaper to ride than gasoline ones. Alternative fuels are not so tightly linked to gasoline price because they are subject to a different tax regime. In 2008 lpg was 35% cheaper to run than gasoline while in 2013 the running cost difference became 40% while cng is on average 70% cheaper to run.

Figure 3: Market share of Alternative Fuel New Cars and filling station density.



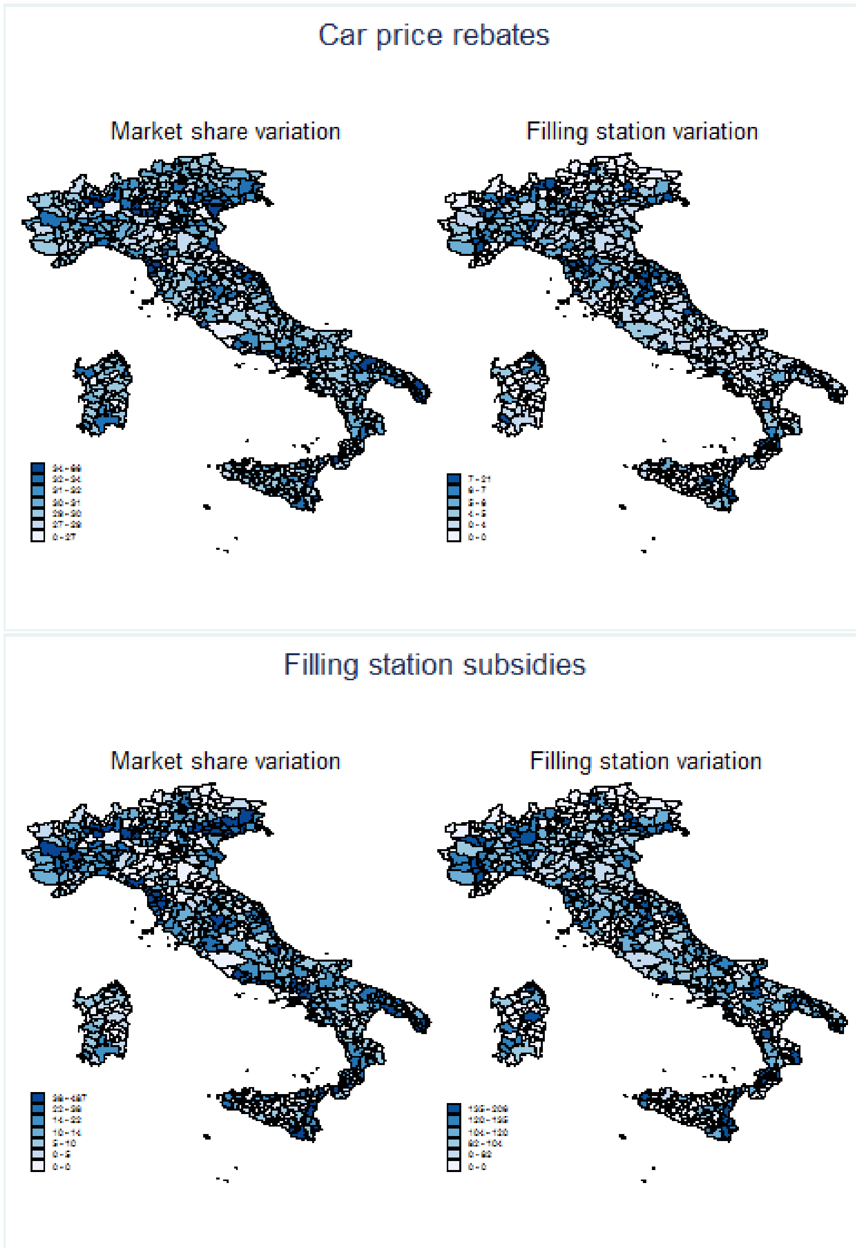
.
Note: The figure shows Italian LMA share of AF cars and filling station density in 2012. The maps above refer to LPG (autogas) cars and filling stations, the below maps refer to CNG (natural gas) cars and filling stations. The maps on the left refer to the market share at market level, the maps on the right refer to the number of the filling stations offering the specified fuel per 100 squared kilometers

Figure 4: Share of new cars 2012 vs pumps per km^2



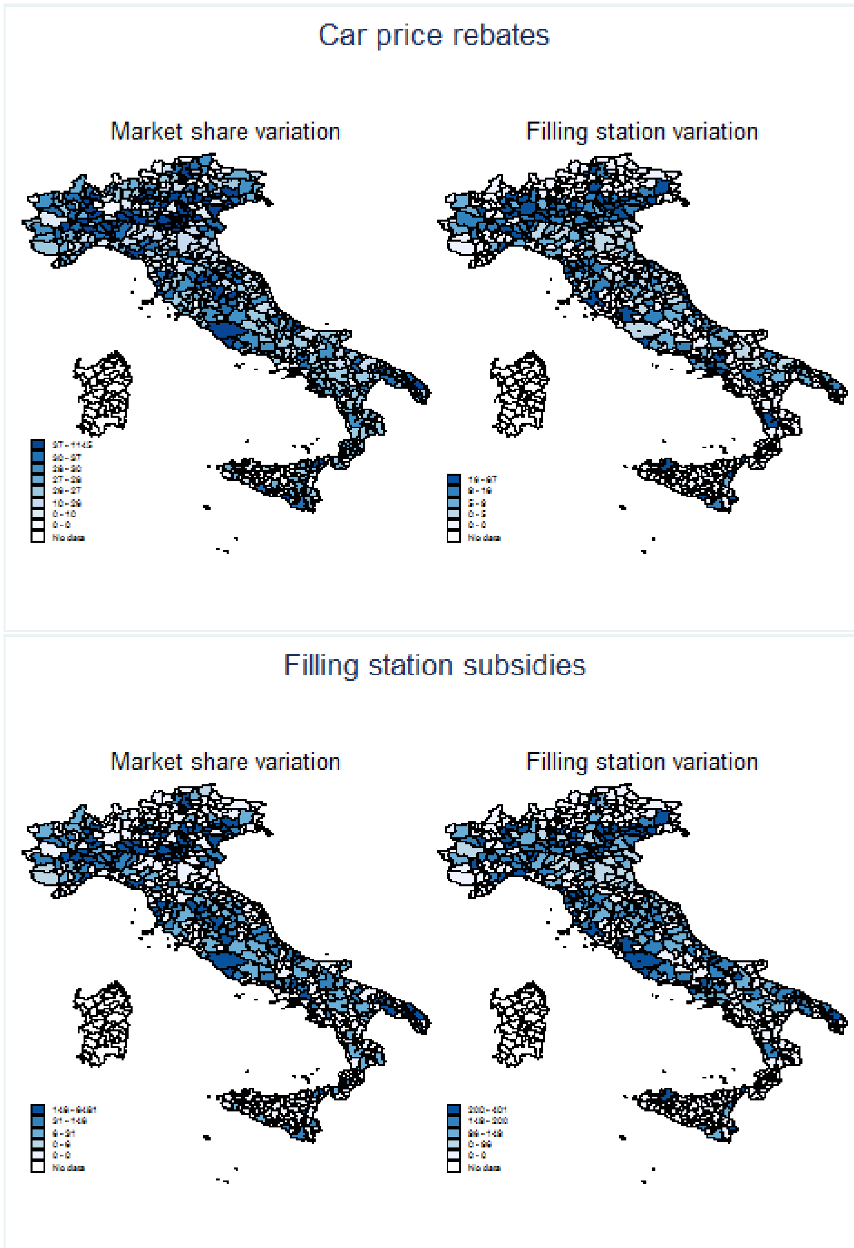
.
Note: The panels report scatterplots between the share of AF cars sold in 2012 and the AF filling stations' density. Each dot refers to a LMA and its dimension is proportional to market dimension. The line refers to the slope of a weighted regression of the share of AF cars on the AF filling stations' density.
The left panel refers to LPG (autogas) cars, the right one refers to CNG (natural gas) cars. There is a significant positive correlation between pump density and market share, this is higher but more disperse for cng than lpg.

Figure 5: Policy experiments:
Market share of LPG New Cars and filling station density variation.



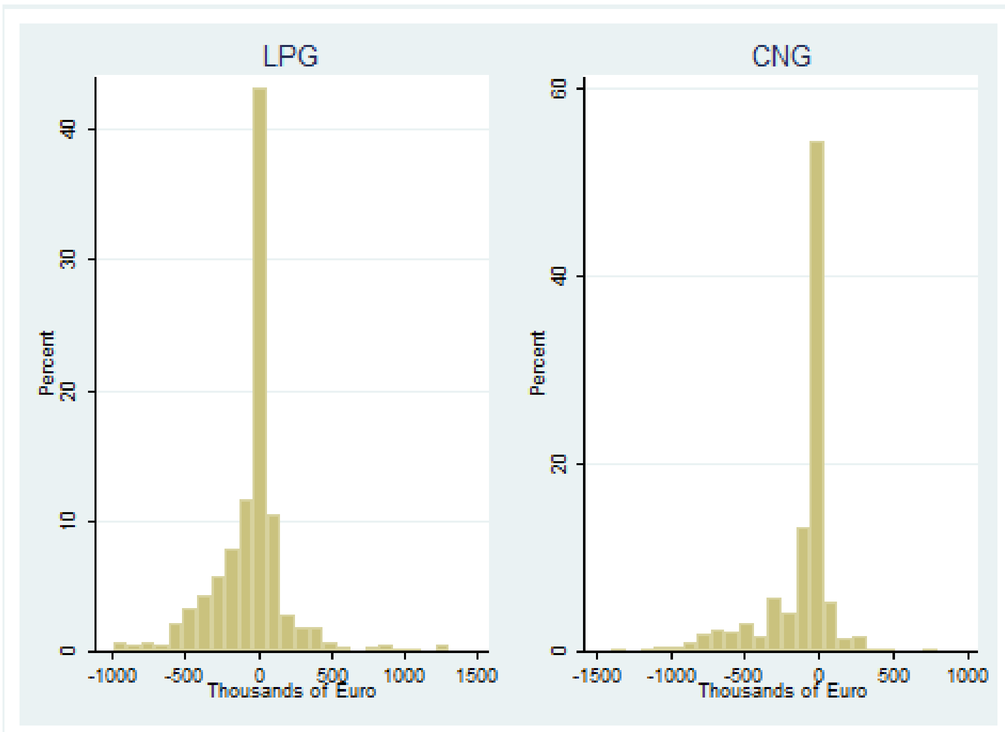
.
Note: The figure shows Italian LMA share of AF cars and in filling station density. The maps above refer to car price rebate effects, the below maps refer to filling station subsiedies effects. The maps on the left refer to the market share at market level, the maps on the right refer to the number of the filling stations offering the specified fuel per 100 squared kilometer

Figure 6: Policy experiments:
Market share of CNG New Cars and filling station density.



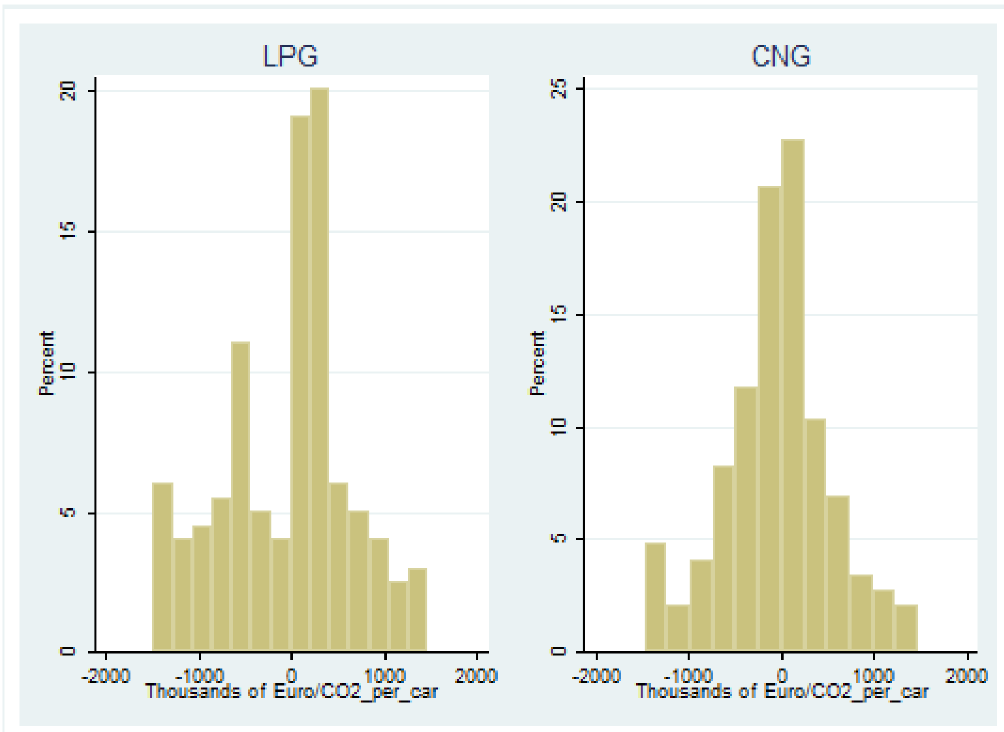
.
Note: The figure shows Italian LMA variation in share of CNG cars and in filling station density. The maps above refer to car price rebate effects, the below maps refer to filling station subsiedies effects. The maps on the left refer to the market share at market level, the maps on the right refer to the number of the filling stations offering the specified fuel per 100 squared kilometers.

Figure 7: Policy experiments:
Cost difference, price rebates vs filling station subsidy



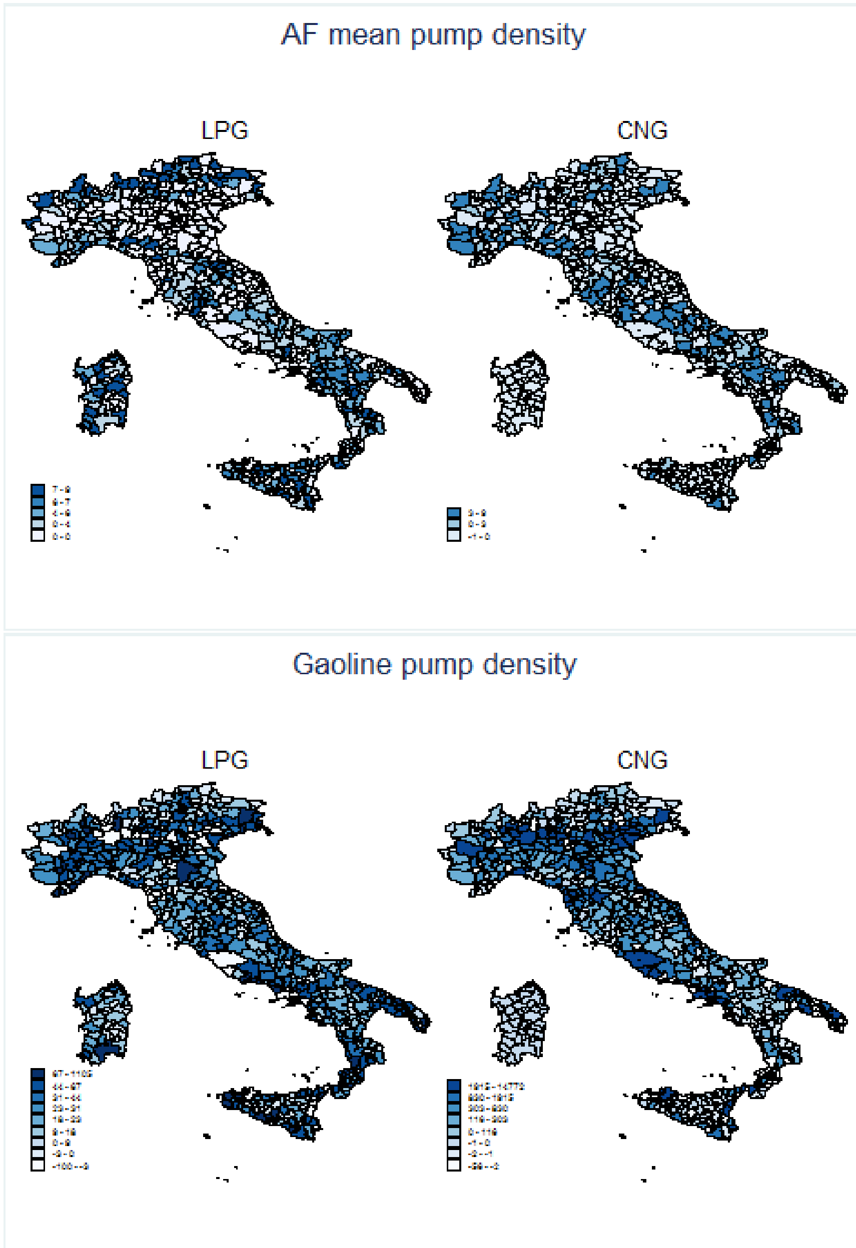
.
Note: The figure shows the distribution of the difference between the cost of the price rebates and filling station subsidy in the Italian LMA. Observations that lies to the left of zero are market in which price rebates are more costly while observations that lies to the right of zero are markets in which filling station subsidies are more costly. The left panel refers to LPG vehicle price rebates and LPG filling station subsidy. The right panel refers to CNG vehicle price rebates and CNG filling station subsidy.

Figure 8: Policy experiments:
Cost effectiveness in terms of CO2 difference, price rebates vs filling station subsidy



.
Note: The figure shows the distribution of the difference between the cost effectiveness in terms of CO_2 per kilometer reduction of the price rebates and filling station subsidy in the Italian LMA. Observations that lies to the left of zero are market in which price rebates are more cost-effective while observations that lies to the right of zero are markets in which filling station subsidies are more cost-effective.
The left panel refers to LPG vehicle price rebates and LPG filling station subsidy. The right panel refers to CNG vehicle price rebates and CNG filling station subsidy.

Figure 9: Setting filling station standards.



Note: The maps report the variation in market composition implied by the filling station stangards. In the top panel, I report the effect of shifting pump density of markets below the average at the average density. In the bottom panel, I report the effect of shifting the pump density at the gasoline pump density level.

Appendix

A Summary statistics

In this section, further insights about the market characteristics are presented. In the Local Market Area (LMA) are sold 36 different brands, belonging to 19 manufacturing groups. In Table A.1 I report some summary statistics about car builders' market share per fuel. Looking at filling station market, in Table A.2 I report the time series of AF filling stations in Italy, while in Table A.3 are reported filling stations by brand and fuel.

Table A.1: Summary statistics - Market share by manufacturer and fuel type.

Car builder group	**Gasoline**	**Diesel**	**LPG**	**Natural gas**
Fiat	9.0 %	7.1%	5.5%	4.7%
Volkswagen	3.8%	8.4%	0.3%	0.2%
BMW	1.19%	2.5%		
GM(Chevrolet, Opel)	3.2%	3.4%	2.7%	0.4%
PSA (Citroen Peugeot)	4.2%	5.1%	0.7 %	
Renault	2.5 %	5.9%	2.1%	
Daihatsu Motor Co., Ltd (Toyota)	3.9%	1.6%		
Ford	2.5%	4.6%	1.1%	
Hyundai	2.9%	3.7%	0.2%	
Mercedes	0.4%	1.5 %		0%
Suzuki	1.2%	0.3%	0%	

Note: The table reports summary statistics on market share for the elven largest manufacturer
I compute the market share over the total number of units sold in 2012 to private owners (863,818).

B Derivation of likelihood function.

Given the primitives of the model, the profitability condition bounds naturally lead to an ordered probit. I can write the log-likelihood according to the distribution of ν_m.

$$\mathcal{L}(\theta) = \sum ln \left(\Phi \left(\frac{ln(vp_m(n_m)) - \gamma W_m}{\omega} \right) - \Phi \left(\frac{ln(vp_m(n+1)) - \gamma W_m}{\omega} \right) \right). \tag{8}$$

Substituting vp with $\hat{vp}$ I get

Table A.2: AF filling stations in Italy. 2000-2013.

year	LPG	CNG
2000	1949	336
2002	2126	402
2006	2311	529
2008	2351	665
2009	2358	693
2010	2364	718
2011	2350	718
2012	3201	896
2013	3275	974

Note: The table reports the time series of the number of AF filling stations in Italy. Sources: ecomotori.net, prezzibenzina.it, Euromobility Report(2007) Quagliano et al. (2009)"Libro Bianco sul metano per autotrazione", "Report on Fuel Distribution Network in Piedmont" (2012).

Table A.3: Summary statistics - Filling stations by brand and fuel

Brand	**Gasoline**	**Diesel**	**LPG**	**Natural gas**
Api-IP	3444	3425	391	67
Eni	4029	4025	677	165
Esso	2331	2329	273	34
Q8	2186	2184	254	30
Shell	688	686	114	22
Tamoil	1476	1469	197	37
TotalErg	2818	2811	308	56
Others and unbranded	2742	2739	856	425
Total	19,714	19,668	3,070	836

Note: The table reports summary statistics on filling station brands.

$$
\mathcal{L}(\theta) = \sum_m ln \left(\Phi \left(\frac{ln((p_m - mc_i)k\frac{1}{n_m}(\hat{q}_m(n_m) + Q_m)) - \gamma W_m}{\omega} \right) \right.
$$
$$
\left. - \Phi \left(\frac{ln((p_m - mc_i)k\frac{1}{n_m+1}(\hat{q}_m(n_m+1) + Q_m))) - \gamma W_m}{\omega} \right) \right). \tag{9}
$$

Consider the number of sold cars q_{mf} in a market m with a given fuel f. Since I consider a nested logit, following Berry (1994), I can compute the market share as:

$$
\begin{aligned}
s_{jm} &= s_{j|mf} s_{mf} = \\
&= \frac{\exp(\delta_{jm}/(1-\sigma))}{D_{mf}} \frac{D_{mf}^{1-\sigma}}{\sum_{mf} D_{mf}^{1-\sigma}}, \\
D_{mf} &= \sum_{j \in f} \exp(\delta_{jm}/(1-\sigma)),
\end{aligned} \tag{10}
$$

where the mean utility is $\delta_{jm} = \alpha p_{jm} + x_j \beta + n_{jm} \lambda + \xi_{jm}$.

The quantity of cars using a given fuel is:

$$
q_{mf} = \sum_{j \in \mathcal{C}_f} s_{jm} L_m. \tag{11}
$$

Using equation (9) and (11) I get the likelihood I maximize to estimate γ.

$$
\mathcal{L}(\theta) = \sum_m ln \left(\Phi \left(\frac{ln\left((p_m - mc_i)k\frac{1}{n_m}(\sum_{j \in \mathcal{C}_f} \hat{s}_j(n_m) + Q_m)\right) - \gamma W_m}{\omega} \right) \right.
$$
$$
\left. - \Phi \left(\frac{ln\left((p_m - mc_i)k\frac{1}{n_m+1}(\sum_{j \in \mathcal{C}_f} \hat{s}_j(n_m+1) + Q_m)\right) - \gamma W_m}{\omega} \right) \right).
$$

C Robustness check

In this section I explore the robustness of my results in demand estimation, considering filling station density endogenous. The idea is that stations and cars' market shares are co-determined. A valid instrument for filling station density is the number of filling stations at the beginning of 2009 since during 2008 the sector was liberalized. I could assume that before 2009 entry choice could happen/not happen even if it was not/was profitable. Therefore, the pre-reform number of

Table C.1: Demand Robustness check. Endogenous pump density

VARIABLES	(1) IV Logit	(2) IV Logit density instruments	(3) IV Nested Logit	(4) IV Nested Logit density instruments
price	-0.21	-0.20	-0.14	-0.14
	(0.0183)	(0.0181)	(0.0141)	(0.0139)
sigma			0.24	0.24
			(0.009)	(0.009)
log(power/weight)	0.01	0.19	-0.13	-0.16
	(0.053)	(0.052)	(0.040)	(0.040)
log(euro/100km)	-0.56	-0.56	-0.54	-0.55
	(0.0264)	(0.0262)	(0.0199)	(0.0197)
log(acceleration)	-1.94	-1.86	-1.34	-1.29
	(0.176)	(0.173)	(0.134)	(0.132)
log(lenghth)	0.19	0.19	0.14	0.14
	(0.013)	(0.013)	(0.010)	(0.010)
lpg*pump/kmsq	0.05	0.05	0.10	0.11
	(0.003)	(0.003)	(0.003)	(0.003)
cng*pump/kmsq	0.39	0.38	0.34	0.36
	(0.011)	(0.011)	(0.008)	(0.008)
diesel*pump/kmsq	0.01	0.01	0.01	0.00
	(0.001)	(0.001)	(0.001)	(0.001)
gasoline*pump/kmsq	-0.01	-0.01	0.00	0.00
	(0.001)	(0.001)	(0.001)	(0.001)
fuelFE	YES	YES	YES	YES
marketFE	YES	YES	YES	YES
monthFE	YES	YES	YES	YES
segmentFE	YES	YES	YES	YES
modelFE	YES	YES	YES	YES
R^2	0.69	0.70	0.83	0.83
mean elasticity	-4.20	-4.02	-3.48	-3.30

Note: Standard errors in brackets.
Column (1) and column(2) report coefficients of logit estimation. Colum(1), endogenous variable, price; column (2), endogenous variables, price and pump density.
Column (3) and column(4) report coefficients of nested logit estimation (nests=fuels). Colum(3), endogenous varibles, price and within nest share; Column(4), endogenous varibles, price, within nest share and pump density.
In column (1) and (3) instruments: "classical BLP" and local legislation alternative duel vehicles demand shifter.
In column (2) and (4) instruments: "classical BLP", local legislation alternative duel vehicles demand shifter and the number of filling stations in 2009 as instruments.

filling stations is exogenous. The relevance of the instrument is suggested by the persistence of the number of filling station during time. I checked the relevance of the instruments computing the F-statistic for each endogenous regressor.