WORKING PAPERS

N° 17-875

December 2017

"Green Car Adoption and the Supply of Alternative Fuels"

Giulia Pavan

Toulouse School of Economics

Green Car Adoption and the Supply of Alternative Fuels.

Giulia Pavan*

December 19, 2017

Abstract

Easy access to stations serving alternative fuels is an obvious concern for customers considering to buy a "green" car. Yet, the supply of fuel is seldom considered analyzing how to promote the adoption of environmentally friendly vehicles. I develop and estimate a joint model of demand for cars and supply of alternative fuels. 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 a more effective policy that indirectly increases low emission car sales.

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

Keywords: Alternative fuel cars; Entry; Environmental policy.

*Toulouse School of Economics, University of Toulouse Capitole, Toulouse, France. E-mail: giulia.pavan@tse-fr.eu. I am grateful to my advisor Andrea Pozzi for his advise and encouragement. I would also like to thank Alessandro Gavazza, Paul Grieco, Marit Hinnosaar, Cristian Huse, Laura Nurski, Mathias Reynaert, Philipp Schmidt-Dengler, Isis Durrmeyer, Margaret Slade, Otto Toivanen, Tommaso Valletti, Jo Van Biesebroeck, Frank Verboven, Michael Waterson, conference participants at EAERE 23rd Annual Conference (Athens, 2017), CEPR IO School/JIE Conference on Applied Industrial Organization (Zurich, 2015), 3rd IAERE (Padua, 2015), 6th ICEEE (Salerno, 2015), EIEF-Unibo-IGIER IV Workshop in Industrial Organization (Bologna, 2014), VII VPDE Workshop (Tourin, 2014), EARIE (Milan, 2014) and seminar participants at University of Tor Vergata (2014), CES-KU Leuven (2014), IRVAPP (2015), CREST (2016), DIW (2016), University of Gothenburg (2016), University of Groningen (2016), TSE (2016) for useful comments. I gratefully acknowledge financial support from the University of Tor Vergata, EIEF and IDEX Chair and the hospitality of KU Leuven. The usual disclaimers apply.

1 Introduction

Promoting the use of environmentally friendly fuels has consistently been a policy priority across advanced economies, given the contribution of transportation to global and local pollution. Yet cars running on new type of fuels need a network of filling stations offering these fuels, which must be developed. Thus, policies aiming to expand the use of alternative fuel (AF) cars must act simultaneously on two fronts: prompting consumers to buy cars running on alternative fuel and increasing the number of refill stations offering such fuels. For instance, in the US the Energy Independence and Security Act (EISA) of 2007 and the European Directive on Alternative Fuel Infrastructure (DAFI) of 2014 recognize the crucial role of infrastructure in the adoption of AF cars. 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 article develops and estimates a joint model of demand for cars and supply of fuels. On the demand side, consumers choose the type of fuel the car runs on, among other characteristics. On the supply side, filling stations must decide whether to install alternative fuel pumps in addition to providing the traditional fuels: gasoline and diesel. The key contribution of this study is modeling customers concern regarding refilling costs, which creates a link between demand of cars and supply of fuels. Consumers take into account fuel price and density of stations when choosing their car. At the same time, filling stations make their strategic choice of installing extra pumps only if the share of alternative fuel cars in the area is large enough. The interdependence between the two sides of the market can be characterized as indirect network effects (or feedback effects), which could cause under-utilization of the network good (see Katz and Shapiro (1994), Ackerberg and Gowrisankaran (2006)).

Cars running on AF, such as liquefied petroleum gas (LPG) and compressed natural gas (CNG), provide a unique opportunity to gain insight into a market with such interconnection between demand and supply. AF cars are more expensive, yet price subsidies make the purchase cost of these vehicles comparable to traditional fuel ones (*demand pull*). At the same time, the supply of fuel is a critical component in the consumers' choice. Alternative fuels are cheaper (consumers would recover the price-premium of AF cars after driving 30,000 to 50,000 km[1]), but less available (15% of traditional fuel filling

[1] I compared car prices and average cost per kilometer of a Fiat Panda and Fiat Punto Evo, using

stations sell LPG and 5% sell CNG). Subsidies to install AF pumps (*supply push*) would soften this barrier to adoption.

My unified framework allows for the comparison of the effects of these policies. The results could also give guidance for policies aimed at fostering similar technologies, characterized by the interdependence of demand for complementary goods. The Italian market is a unique setting, which is characterized by a high market share of LPG and CNG cars as well as a sizable network of filling stations. Namely, in 2012 the two fuels accounted, respectively, for 12% and 6% of new cars sold, and, on average, 5 filling stations per local market sell LPG and 2 sell CNG.

I assemble a novel dataset which is uniquely suited for studying the relationship between car adoption and fuel availability, merging information from several sources. I collected data on car sale price, fuel type and other characteristics for newly purchased cars by private holders. I combine them with information on location and range of fuels offered by the universe of filling stations active in 2012 in Italy. I exploit differences in local legislation relative to traffic limitations for traditional fuel cars, reduced taxes for AF vehicles, and laws imposing filling stations to supply at least one alternative fuel as shifters of the benefit of adopting an AF car.

The 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, nesting cars of the same fuel type/segment as closer substitute. The main takeaway of the demand model is that consumers are highly sensitive to fuel availability. Increasing the density of alternative fuel filling stations by 1% leads to a 6% increase in the market share for AF cars.

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 demand estimated in the first step of the model. This allows me to capture the network effect on filling station profits.

I use the demand and entry estimates to simulate the effects of two alternative policies designed to boost AF car adoption, keeping government expenditures equal: a car price rebate (1,700€) and a subsidy for filling stations (reducing their fixed costs by 60%). The

average fuel prices in 2012. ACI and Censis (2012) estimated that 11,000 kilometers per year are run by average cars. That is, 2 to 4 years are needed to recover the price premium of the AF car.

results show that subsidizing fuel retailers to offer AF is an effective policy to indirectly increase AF vehicle sales through their direct effect on pump adoption by traditional fuel filling stations, while price subsidies have negligible effects both on AF sales and pump installation. This is because AF pump density influence consumers' vehicle choice more than price. These results also imply a more persistent effect of the supply push policy versus the demand pull one.

This article contributes to the literature looking at the determinants of adopting alternative fuel cars. 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. 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. This article proposes a fully-fledged demand and supply model to study the incentives to alternative fuel adoption, contributing as well to the literature that studies the indirect network effect of policies on fuel availability (Shriver, 2015; Li et al., 2017; Springel, 2017).

The policy question addressed in this article, relates to the vast literature on government intervention to limit fossil fuel consumption and promote green fuels. For instance, there is a 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 this literature examines the effect of standards (e.g. CAFE regulation in the US) on new car adoption (Goldberg, 1998; Austin and Dinan, 2005; Reynaert, 2017), used car adoption (Jacobsen, 2013) and the effects of federal income tax incentives on the demand for hybrid vehicles (Beresteanu and Li, 2011). This article compares traditional policies (car subsidy) with less explored policies aimed at expediting the adoption of alternative fuel cars by taking advantage of feedback effects of fuel infrastructures (filling station subsidies).

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

[2]See Allcott and Greenstone (2012) for a recent detailed review. More recently, Allcott and Wozny (2014) and Grigolon et al. (2017).

2 Background and data

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 Liquefied Petroleum Gas (LPG), or autogas, which comprise the bulk of the market in Italy. These fuels are used in traditional gasoline/internal combustion engine automobiles that have been modified, which are bi-fuel vehicles that can also run with gasoline. I include in my analysis only sales of new vehicles to private owners, converted by the manufacturers into AF vehicles and covered by warranties. Although these fuels differ in nature and environmental impact, most of them not only produce less tailpipe pollution and CO_2,[3] and they can also be significantly cheaper to run.

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.[4] The market share of these types of cars is historically higher in Italy than in the rest of Europe: in 2013 77% of CNG European cars and 26% of LPG ones were registered in Italy. In recent years, both demand pull and supply push policies have been implemented. In 2009, the green car market benefited from generous incentives [5] in the form of a scrappage scheme. On the filling station side some regions[6] subsidized filling stations for installing alternative fuel pumps in 2014 and 2015. Yet, it was the liberalization of the retail fuel market[7] and the simplification of authorization and bureaucracy for the opening of new pumps [8] that led to the development of a sizeable network of filling stations. Most of CNG filling stations are directly linked to the pipelines.[9] However, in case a filling station is located in an area

[3]CNG has very low particulate emissions, it produces less carbon dioxide than diesel and it has lower NOx emissions. LPG is derived from natural gas processing or oil refining, with a lower carbon footprint and significantly less pollutant emissions than conventional fuels.

[4]Filling stations in 2011 were 3,110 (2,350 LPG and 760 CNG) while in 2013 they were 4,249 (respectively, 3,275 and 974. Data: Ecogas consortium and ecomotori.net.

[5]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 or CNG.

[6]Liguria, Piemonte and Lombardia

[7]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 liberalizes the sector and incentivize modernization. See Pavan et al. (2017) for further details.

[8]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. For more details on the CNG retail industry see Pavan et al. (2017).

[9]All but a few pipelines are owned and operated by SNAM Rete Gas

without a pipeline, CNG can be stored and distributed in hard containers transported onto trucks and semi-trailers. While LPG is delivered to a station by a transport truck and stored in tanks. Manufactured during the refining of petroleum (crude oil), it is mostly produced in the Italian refineries.

[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 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 a decrease of new car registrations in the Italian market since 2007. The peak in 2009-2010 can 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 entire sector was subsidized, only the additional incentives dedicated to AF cars seem to affect the quantity of new cars, and the effect on LPG cars is much stronger than on CNG cars.

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. As pointed out in Schiraldi (2011), scrappage scheme induce only early replacement of vehicles, boosting aggregate sale for one year and contracting them for the following years. In this article, I look at a different mechanism, whether price incentives are more effective in markets were filling stations density is higher, which explains why LPG cars market share increase more than CNG one.

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, while LPG is always cheaper than gasoline and sometimes very close to diesel. Moreover, gasoline and diesel prices show an increasing trend, while AF price trends are more stable. Notice that alternative fuels are subject to a different tax regime from traditional fuels, which contributes to widening the cost differences.

[Figure 2 about here.]

Figure 3 shows the diffusion of alternative fuel cars across the country (for privately-owned cars only). LPG cars are sold all over the country while CNG cars are concentrated in certain 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 so dispersed (the LPG and CNG price in 2012 were respectively 0.83€/*liter* and 0.98€/*kilgram* with a standard deviation of 0.053 and 0.037).[10] Geographical differences play a stronger role in the heterogeneous development of AF networks. Namely, mountainous regions are not covered by networks and southern ones never developed a CNG network. In Sardinia, the lack of a local pipeline hindered the development of a local CNG network, while in the rest of southern Italy the network did not develop due to lack of local investments. In mountainous regions, pipelines are less accessible. Furthermore, the maps show the first evidence of a strong correlation between AF car shares and pump density, which is also confirmed in Figure 4, where scatterplots between the share of AF cars sold in 2012 and AF filling station density are presented. It shows the strongly significant positive correlation which will be further investigated in what follows.

[Figure 4 about here.]

The last characteristic of the Italian market that fits the entry model I present later, is related to the ownership/management of filling stations. As underlined by the Italian AGCM (Autorità Garante della Concorrenza e del Mercato) in its 2012 report on the retail gasoline market, independent filling stations (a.k.a. white pumps) are more likely to install CNG and LPG pumps.[11] In fact, a major difference between the unbranded and branded is that the former can have distinct contracts with fuel brokers for each type of fuel. As the markup for LPG and CNG is higher, white pumps have stronger incentives and weaker barriers to install AF pumps. Thus, I later assume in the entry model that markets are independent and possible scale effects are negligible.

[10]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.

[11]In the data we observe that 20% of filling stations offering traditional fuels are white pumps. If we look at filling stations offering AF the percentage of white pumps increase up to 55%.

Data

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

Automobile sales, prices and characteristics

I obtain car sales at the municipality level from the vehicle registration database, maintained by *Automobile Club d'Italia* ACI (vehicle registration is mandatory in Italy). I focus on private purchases and drop corporate car purchases, which yields 882,641 cars sold in 2012. The level of observation is a variant, defined as the combination of make, model, body type (including doors) and engine displacement.[12] I observe sales in 572 markets area in 2012. Such a disaggregation leads to many variant/market combination with no sales. Prices and other characteristics have been collected from industry publications, ("*Quattroruote*" and "*Panoramauto*"). The price information includes the list price and the registration tax (IPT), which vary at the local level.[13] Other car characteristics I observe are: horse power, type of fuel, fuel consumption, tank and trunk capacity and acceleration time from 0 to 100km/h. Moreover, I distinguish among seven market segments: subcompact, compact, intermediate, standard, luxury, SUV and sport.

The databases report data at different levels of aggregation, so I match car sales with price and characteristics of the standard equipment.[14]

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 Italian filling stations. For the 19,892 filling stations active in Italy in 2012, I observe the fuels they offer and their location, and use the date in which they entered the database as a proxy for their date of market entry. I cross-checked 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

[12] 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).

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

[14] Performance characteristics are the same for all the equipments since the engine is the same.

(AGCM, 2013).

I aggregate data at market level, considering Labour Market Areas (LMAs) as a market.[15] 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.[16] They are designed to obtain meaningful and comparable sub-regional labour market areas. However, they can easily be adapted to define to define fuel markets, given their functional definition based on commuting patterns.[17] I aggregated the smallest areas and obtain 572 distinct areas.

Summary statistics

Table 1 reports summary statistics on vehicle characteristics weighted by sales, reported by fuel.

[Table 1 about here.]

On average, diesel cars are more expensive than AF cars, since 20% of its market share are SUV cars, which are more expensive than sub-compact, compact and intermediate cars. If we compare the price of cars by model, AF prices are higher than gasoline ones. Namely, LPG cars are about 10% more expensive, while CNG cars are 15% more expensive. But most AF models sold are mainly sub-compact, compact and intermediate cars. I also report data on CO_2 emissions (as declared by manufacturers), but I do not have data on PM and NOx by model. While CNG cars emit less CO_2 than both gasoline and diesel, LPG CO_2 emission levels are comparable to diesel ones, although they emit less local pollutants.

[Table 2 about here.]

Table 2 reports summary statistics of the variable used to compute variable profit (fuel sold per car, fuel prices, stock of cars, and number of pumps), the expected variable profit and cost shifters (log of refinery distance in case of LPG and to log of numbers of connections to the pipeline in case of CNG).

[15] Local labour systems, SLL in Italian.

[16] 2011 LMAs are based on commuting data stemming from the 15th Population Census.

[17] LMAs are designed to respect only municipality administrative boundary constraints: 56 of them cut across regional boundaries and 185 span across different provinces. 85% of inter-provincial provinces are characterized by a prevalent province in which are concentrated more than 80% of the observations.

3 Empirical Model

The empirical model describes consumer demand for cars and filling stations' choices of entry in the AF retail industry. 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.[18]

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

Demand

I consider $m = 1, ..., M$ local markets (LMA), each with $h = 1, ..., H$ households. Each household chooses whether to buy a vehicle among the set of $j = 1, ..., J$ cars available in the market or not to buy any. Consumers maximize a utility function linear in parameters. I define the indirect utility of a household h in market m from buying a car model $j(f)$ running on fuel f, as a function of product characteristics, fuel availability and utility parameters to be estimated.

$$u^h_{j(f)m} = \delta_{j(f)m} + \nu^h_{j(f)m} \tag{1}$$

The first part of the equation is the mean utility, common to all the households, which I specify as:

$$\delta_{j(f)m} = \alpha p_{j(f)m} + x_{j(f)}\beta + n_{fm}\lambda + \xi_{j(f)m} \tag{2}$$

where $p_{j(f)m}$ is the price of a car model j installing fuel f in market m. Notice that the price is indexed by m because the presence of local taxes makes it market specific.

[18]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). For a detailed overview of the literature, see Busse et al. (2013)

The vector $x_{j(f)}$ includes car characteristics as well as the fuel costs, and n_{fm} is the fuel availability (which in the main specification will be fuel density), which varies by market and fuel type. $\xi_{j(f)m}$ refers to unobserved (to the econometrician) car characteristics.
The error term is modeled as in Verboven (1996), it follows the distributional assumption of a two-level nested logit model, which allows preferences to be correlated along two discrete product dimensions: the fuel cars run on and the segment they belong to.[19] The upper level of the nesting structure consists in the choice between different type of fuels (gasoline, diesel, lpg or cng) or the outside option of not buying a new vehicle, this mirrors the consumers' preferences towards specific fuel-type cars and, in particular for AF cars, it captures the willingness of consumers to face extra-costs related to adapting driving pattern to filling station locations. This assumption is based on anecdotal evidences reported by experts of the sector (*metanoauto.com, Quattroruote*), they suggest that fuel-type is an upfront decision and it is not captured by the other variables. The utility of the outside good (not buying a car) is normalized to zero. Following Goldberg and Verboven (2001), I use market segment (e.g. compact, intermediate, SUV etc.) as the other dimension of differentiation characterizing demand. The individual specific part of the utility given by car j in market m is:

$$\nu^h_{j(f)m} = \varepsilon^h_{fm} + (1-\sigma_2)\varepsilon^h_{sfm} + (1-\sigma_1)\varepsilon^h_{jm} \tag{3}$$

where ε^h_{fm}, ε^h_{sfm} and ε^h_{jm} have extreme value distributions (Verboven, 1996). The distributional assumptions imply a simple formula for the aggregate demand for car j in market m, belonging to segment s and fuel f:

$$s_{jm} = \frac{e^{\delta_{jm}/(1-\sigma_1)}}{e^{I_{sfm}/(1-\sigma_1)}} \frac{e^{I_{sfm}/(1-\sigma_2)}}{e^{I_{fm}/(1-\sigma_2)}} \frac{e^{I_{fm}}}{\sum_{f=0}^{F_m} e^{I_{fm}}}, \tag{4}$$

where I_{sf}, I_g; I are individual "inclusive values" as defined in McFadden (1978): $I_{sf} = (1-\sigma_1)ln\sum_{j=1}^{Jsf} exp(\delta_j/(1-\sigma_1))$, $I_g = (1-\sigma_2)ln\sum_{s}^{S_f} exp(I_sf/(1-\sigma_2))$ and $I = ln(1+\sum_{f=1}^{F} exp(I_f))$. The nesting parameters capture the preference correlation within cars with the same fuel (σ_2) and with the same fuel/segment (σ_1).

[19] 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). This assumption allows me to consider the fuel nests not overlapping.

Entry

The density of filling stations offering a particular type of fuel is determined by an entry model. Filling stations selling traditional fuels choose whether or not to enter the alternative fuel market by adding a pump for an alternative fuel. I model this choice as a game of complete information in the spirit of Bresnahan and Reiss (1991). I consider the AF retailing market as a homogeneous good industry and assume that all the filling stations operating in 2012 are potential entrants into the AF market. Post entry profits accruing to firm i from offering an alternative fuel in market m take the following form:

$$\Pi_{im}(n_m) = \underbrace{(p_{im} - c_{im})l_i(p_{im}, p_{-im}, n_m)}_{VP_i(n_m)} - F_{im} \tag{5}$$

where p_{im} is the price per unit (liter for LPG and kilogram for CNG) at which the firm sells the fuel and c_{im} 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, firm i 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 a number of simplifying assumptions similar to those in Berry and Waldfogel (1999):

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

$$l(q(n_m)) = \frac{1}{n_m}[k_m(q(n_m) + Q_m)] \tag{6}$$

  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

[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.

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.

Hence, I can rewrite profits in a given market as $\Pi_m = (p-c)l(q(n_m)) - F_m = VP_m(q(n_m)) - F_m$.

4 Identification and Estimation

Demand

In order to estimate the demand parameters $\theta = (\alpha, \beta, \sigma_1, \sigma_2)$, I first express the logarithm of the ratio of the market share of car j and the market share of the outside good, s_0, generalizing Berry (1994) as in Verboven (1996); Björnerstedt and Verboven (2016).

$$\ln\left(\frac{s_{j(f)m}}{s_{0m}}\right) = \alpha p_{j(f)m} + x_{j(f)m}\beta + n_{fm}\lambda + \sigma_1 \ln s_{j(f)|sfm} + \sigma_2 \ln(s_{s|fm}) + \xi_{j(f)} \quad (7)$$

where $s_{j(f)|sfm}$ is the market share of product $j(f)$ in segment s installing fuel f, and $s_{s|fm}$ is the market share of segment s cars installing fuel f. In the demand specification I include both physical (length) and performance characteristics (ratio of power over weight). Moreover, I have two characteristics that vary across markets: fuel cost for 100km, computed as the product of fuel efficiency of the car (kilometers per liter) and the average annual price of the fuel the car runs on observed at province level; fuel availability, computed as the logarithm of the number of dealers per square kilometer.[22] Moreover, I interact fuel availability with a dummy for AF models in order to capture differences in fuel availability. The intuition is that traditional fuel cars are chosen without taking into account the density of their filling station since it is so high that it is not a concern. When the consumer decides to switch to an AF cars, though, she takes into account the extra cost of refueling. I also include in the specification fuel type, car model, and regional fixed effects as well as market level variables such as population density, average income and altitude zone, which explain the remaining variation.

I take advantage of local taxes in order to compute prices $p_{j(f)m}$ by market. Moreover, I take into account the endogeneity of price and market share of product $j(f)$ within

[22]In Appendix B I also report the results with different definition of fuel availability, as suggested in Nurski and Verboven (2014).

group f and subgroup s. As is standard in the literature (Berry, 1994; Verboven, 1996; Train and Winston, 2007), I use a set of polynomial basis functions of car characteristics within fuel and market segment.[23] Moreover, I include two shifters of AF vehicle demand, driven by local legislation: a dummy variable equal to one if at least one municipality in the LMA in 2010 suspended the circulation of vehicles except alternative fuel ones for at least one day,[24] and a dummy variable equal to one if the region provides annual tax exemptions only for AF cars. These are demand shifters that affect only the CNG and LPG nests and not the utility of a specific j model. The value of the F-statistic of the first stage is strong.

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), the density of filling stations is an exogenous variable. However, filling stations did not install all the AF pumps in 2011 but over years. I take into account such timing issues in a second specification of the demand model, instrumenting the density of AF filling stations using their density in 2006 when the sector was not fully liberalized yet, the number of connections to the pipeline (this is a proxy of the availability of the pipeline in that market) and the distance from refineries producing LPG. Under both specifications, I assume that filling stations observe the realization of demand only when it has already installed the AF pump. As in Eizenberg (2014), firms are able to forecast only the systematic effects of cars characteristics and filling station availability (for which I control) on market share, therefore their choice of entry is not correlated with $\xi_{j(f)}$ but only with its distribution.

Entry

Given the point estimate $\hat{\theta}$ obtained in section 4, it is possible to separately identify fixed costs parameters. In a free entry equilibrium, firms enter the market until it ceases to be

[23]Instead of fuel costs, fuel efficiency is used as exogenous characteristic.

[24]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 $http://www.anci.it/index.cfm?layout=dettaglio\&IdSez=10325\&IdDett=22223$

profitable. These conditions can be written as:

$$E_{\xi|\theta}(VP_m(n;\xi,\theta) > F_m \text{ and } E(\xi|\theta)(VP_m(n+1;\xi,\theta) < F_m \tag{8}$$

$VP_m()$ denotes the variable profits of firms in market m if there are n entrants, and the expectation is taken over the true distribution of the error term of the J products.
I then assume the following structure for the logarithm of the fixed cost of entry in market m:

$$ln(F_m) = \gamma W_m + \omega\nu_m \tag{9}$$

where γ and ω are parameters to be estimated and ν_m is a standard normal error. W_m is a vector of market specific observable cost shifters. Namely, I include market size proxies such as population density and geographical dummies, as suggested in Bresnahan and Reiss (1991). Moreover, I include a dummy identifying the presence of regional laws requiring filling stations to supply at least one alternative fuel, the distance from refineries for LPG, and the number of connection to the pipeline in the market for CNG.

Equations (8) and (9) imply that n_m entrants in market m are consistent with the following inequalities.

$$\frac{ln(E_{\xi|\theta}(VP_m(n_m+1;\xi,\theta)) - \gamma W_m}{\omega} \leq \nu_m \leq \frac{ln(E_{\xi|\theta}(VP_m(n_m;\xi,\theta)) - \gamma W_m}{\omega} \tag{10}$$

The distributional assumption on ν_m imply the following log-likelihood for the event that n filling stations decide to offer an alternative fuel in market m:

$$\mathcal{L}(\theta) = \sum_m ln\left(\Phi\left(\frac{ln(\widehat{VP_m}(n_m)) - \gamma W_m}{\omega}\right) - \Phi\left(\frac{ln(\widehat{VP_m}(n_m+1)) - \gamma W_m}{\omega}\right)\right) \tag{11}$$

$\widehat{VP_m}(n_m) = (p_m - c)\left(\frac{1}{n_m}(k_m(\hat{q}(n_m) + Q_m))\right)$ is the vector of variable profits quantified using different data sources: I use data from the ACI on the stock of existing cars Q_m by fuel in each market and information provided by the Ministry of Economic Development and *Federmentano* on average AF consumption(k_m). In order to compute markups, I use information on prices at the local level, while marginal costs are considered constant at the national level and are chosen according to provisional profit and loss accounts available on on-line forums and confirmed by pump producers (toil.spa) and pumps owners, taking into account national taxes. As variable profits depend on the unobserved component ξ, I numerically integrate it using 100 J-dimensional vectors from the distribution of ξ obtained as a result of the demand step. The parameters of the fixed cost function, γ, are estimated from maximize likelihood (see Appendix A for further details).

In W_m I include population by market, the macro region in which the filling station is installed, the presence of a regional law imposing the supply of at least three fuel type for new filling stations (it does not apply to most of the new entries which are already existing filling stations adding an extra pump, however it captures a higher interest in that region towards these type of vehicles), and cost shifters related to transportation costs (the number of connections to the pipeline, which is a proxy of the availability of the pipeline in that market, and the distance from refineries producing LPG).

Equilibrium

The equilibrium of the model is given by n^* and q^* that satisfy equation (8), given demand and entry parameters identified in equations (7) and (11). A sufficient condition for the equilibrium to be unique is 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 (see Appendix A for further details), so this condition does not hold for all positive n[25] and the model has multiple equilibria. HIt is important to notice that, 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.[26]

5 Empirical Results

Demand

In Table 3 I report the coefficients estimated using a two stage IV nested logit. In column (2) I report the demand estimation results instrumenting AF filling station density as

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

[26] Reguant (2016) proposes a new methodology to allow counterfactual analysis with multiple equilibria, computing the bounds of a given outcomes. This bounds method could be also used to show that the equilibrium is indeed unique.

discussed in Section 4.

[Table 3 about here.]

Price has a significant and negative impact on consumers' mean utility. The implied average own-price elasticity in the two specifications is -4.45 and -2.88, which is in line with other estimates of the European car market (Goldberg and Verboven (2001)).

In general, all coefficients have the expected signs and are tightly estimated. The power/weight and length of the car have a positive and significant effect on mean utility, while the fuel cost coefficient is negative and significant, as expected, although small in magnitude. These results indicate moderate undervaluation of fuel costs by European consumers as shown in Busse et al. (2013) and Grigolon et al. (2017).

AF availability parameters ($log(N/M) * AF$, where M is the surface of the market in squared kilometers) are positive and significant in both specifications, even considering AF availability endogenous, there is a positive relationship with cars demand. Table 9 presents parameter estimates under an alternative measure of fuel availability: the nearest retailer distance. In that case we have negative and significant coefficients, meaning that the further is the closest filling station, the less the consumer would adopt alternative fuel cars. The coefficient of fuel availability for the base category (traditional fuel cars) is less clear: as expected it has lower magnitude but it also becomes negative when we instrument for AF availability. These results are consistent with the hypothesis that filling station density is not a relevant characteristic for adopting tradition fuel cars since they are the standard type of vehicles consumers would choose while she would take into account this characteristic in case of purchasing AF vehicles.

The nesting parameters are significantly different from zero. Moreover, the hypothesis that the nesting parameters are equal is rejected at the 5% significance level. The restrictions for consistency with random utility maximization in a nested logit $1 \geq \sigma_1 \geq \sigma_2 \geq 0$ are satisfied (McFadden et al., 1973). The results imply that consumer preferences are more strongly correlated within groups.

Entry

Table 4 reports estimates of the parameters of an ordered probit obtained by exploiting post-entry information on variable profit, holding demand estimates fixed. The estimated coefficients characterize the mean distribution of the log fixed costs. Taken as reference the north western macro region, fixed costs are lower in the islands[27] for both fuels, while in the other macro-regions the coefficients have opposite signs for the two fuels. The fixed costs are higher in more populated markets, this could reflect the higher cost of input, while the cost shifters used in the regression have no significant effect. The estimated standard deviation of log fixed costs ω are equal to 0.60 (LPG) and 0.63 (CNG), which implies a fixed cost variance depending on market characteristics more than half of the mean fixed cost.

[Table 4 about here.]

To measure the fit of the model in the data, I compare the number of filling stations implied by the model with the observed ones. I draw 1000 vectors of fixed costs by their distribution and I compute the number of filling stations that would fulfill condition (8). The correlation between this number and the observed number of filling station is 0.84 for LPG and 0.90 for CNG.

6 Policy experiments

Car price rebates vs. filling station subsidies

I use the structural model described so far to compare the effect of different policy incentives to adopt alternative fuel vehicles. I compare the effects on AF cars adoption 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*).

In order to compare the two policies, I set a price rebate and a filling station subsidy that are roughly equivalent in terms of government expenditure.[28] In particular, the price

[27]for CNG Sardinia is not included since there is no CNG pipeline and its insularity and distance from the cost does not allow to connect to the Italian pipeline. In Sicily there is both the CNG pipeline and LPG refineries.

[28]In order to compute government expenditure for the price rebate, I simulate the number of AF vehicles that would have been sold if the price rebate was in place. The overall government expenditure is given by the number of AF vehicles times the magnitude of the price rebate. In the case of filling station subsidy, I computed the number of filling stations that would add an extra AF pumps for different percentage reduction of average fixed costs. As the entry model allows me to vary the fixed cost parameter in relative terms and not to estimate it in absolute term, I calibrated the government cost under the different fixed costs reduction scenarios, using fixed costs reported from the expert of the sector. Thus, I obtain total government costs multiplying the fractions of fixed costs covered by the government times the number of filling stations that would enter if the policy was in place.

rebate is 1,700 €, while filling station would receive 60% reduction of their fixed costs. The price rebates are in line with the 2009 Italian rebate program and other European scrapping schemes (Schiraldi, 2011; Huse and Lucinda, 2014; Grigolon et al., 2016). [29] Also the filling station subsidies are coherent with policies implemented in 2014-2015 in some regions of Italy.[30] The two policies imply a government expenditure of about 270 millions of euro for LPG and 300 millions of euro for CNG.

I distinguish between a "direct effect" and an "overall effect" of the two policies. In the case of demand push policy, the direct effect is the result of a price rebate on the market share of AF cars. Computing the overall effect, I take into account the feedback of the policy on filling stations. That is, I compute the number of stations that would install an extra AF pump due to the extra demand of fuel, and the effect of new AF filling stations on AF vehicles market share.[31] The direct effect of filling station subsidy is the increase in number of pumps. Also in this case I take into account feedback effects to compute the overall effect. Therefore, I compute the new cars quantities and filling stations that satisfy the entry condition (8) after the policy introduction. 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.

[Table 5 about here.]

Table 5 reports the average percentage difference between the estimated market shares under the baseline model and price reduction of LPG car by $1,700$€ compared with a filling station subsidy equal to 60% of fixed costs. The "direct effect" of the first policy implies an increase in LPG market share by 2%. The effect of the policy on other fuel type cars market share is small (-0.03%). That is, the extra market share of AF cars mainly comes from the outside good. Looking at the "overall effect"of the price rebate,

[29] In Italy the scrappage scheme involved rebates for purchase of both traditional and alternative fuel cars, the latter, however, were more generous. 1,700€ is the approximate difference in the rebates for the two type of cars.

[30] 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.

[31] In order to take into account the possible feedback effect on filling stations choice of installing AF pumps, starting from $n = 1$, I jointly compute $\widehat{q(n)}$ and $\Pi(\widehat{q(n)})$ increasing n until the entry condition (8) is satisfied.As pointed out in Section 4, I verified that within the domain there is a unique equilibrium. Therefore, I am not worried to select an equilibrium.

LPG vehicles market shares marginally increase given the negligible effect that the policy has on filling station entry choices. On the other hand, the filling station subsidy leads an higher increase of both LPG market share (48%) and pump density (the overall effect is an increase of 111% of filling stations serving LPG). The main driver of the choice of entry is the reduction of the fixed cost, which induces an increase of filling station density by 90%. The high importance that consumers place on the availability of filling stations showed in demand results explains the effectiveness of the filling station subsidy in terms of LPG vehicles adoption. Also in this case, the extra market share of AF cars mainly comes from the outside good and not from a substitution effect, as shown by the high nesting parameters.

[Table 6 about here.]

Table 6 reports the average percentage difference between the estimated market shares under the baseline model and price reduction of CNG car by 1,700€ compared with a filling station subsidy equal to 60% of fixed costs. In the case of CNG vehicles price rebate, reported in the left table, the effect of the policy is similar to the LPG case (about 2%). Also in this cas, the very low effect on market share does not lead the entry of filling stations. The right table reports the variation in AF pump density and vehicles market share after a decrease of the fixed costs of installing a pump by 60%. Looking at the difference between "direct" and "overall" effects of the policy, the feedback effect due to the increase in circulating cars leads to an extra increase of 20% in filling station density. The overall effect of the policy on the market share (35%) is stronger than the price rebate one and it is due to the high elasticity of CNG pump density.

The variability of the results suggests an heterogeneous effect of policies across markets: in general, the markets with highest number of circulating cars and existing filling stations are more reactive to both policies. 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 uneven.

[Figure 5 about here.]

[Figure 6 about here.]

For the reason that the adoption of alternative fuel cars should induce a reduction in CO_2 emissions[32] per kilometer run by cars, I present a back-of-envelope calculation of these reductions under different scenarios. The lack of substitution between traditional and alternative fuel cars implies that such policies slightly decrease the average CO_2 per kilometer emitted by new cars. Only the filling station subsidy policy reduce the CO_2 per car, showing again high variability among markets.

[Table 7 about here.]

Results are shown in Table 7. Both policies have very small effect on the fleet composition in terms of CO_2 emitted per car since, even if the market share variation is quite big, AF cars remain a small share of the market (15% LPG and 8% CNG). 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.

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 also more persistent.

Filling station standards

In the second counterfactual, I simulate the effect of a mandate on the density of filling stations. An example of such a policy is the European Directive No.94(2014) that "sets out minimum requirements for the building-up of alternative fuels infrastructure". As 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

[32]LPG and CNG cars produce, on average, respectively 2.5% and 9.3% less CO_2 emissions with respect to gasoline cars. 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.

density. Moreover, I compute the effect of increasing AF pump density imposing them equal to the gasoline pumps density in the market. Results are reported in Table 8

[Table 8 about here.]

The impact of the increase of AF pump density at the average level on AF vehicles market shares is coherent with filling station subsidy results. In fact, the average density of LPG and CNG filing station is respectively 1 and 0.5 pump every one hundred squared kilometers. 270 markets have a density of LPG filling station below the average while for CNG I vary the density of filling stations in 250 markets, I simulate what would be the market share of cars per fuel in this setting. The average increase in LPG cars is 30%, taking into account that our policy imply an average increase bt about 67%, this result is coherent with the ones reported for the filling station subsidies. In this scenario, I am looking at the joint effect of the policy, thus I allow for substitution between AF vehicles which implies some substitution effect from LPG to CNG as well. This explains why LPG market share could decrease by 0.64% in some markets. Similar results are obtained for CNG, where the market share increases by 25% lead by an increase of pump density by about 50%.

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). In this extreme example the pump density of LPG is increasing on average by 194% while CNG one by 350%. Thus, this is clearly an out-of-sample simulation meant to underline how the market share of AF vehicles is sensitive to filling station density and the substitution pattern between different vehicles is relatively small. In the table are reported the variation in terms of market share, however, if we look at the absolute number of cars bought in this scenario, we will find that LPG cars would reach diesel level and CNG cars gasoline ones.

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, keeping government expenditure fixed. Then, I consider the effect of increasing filling station density to different standards.

On the one hand, I find that price rebates partially foster the use of AF cars, not being able to push filling station owner to install AF pumps. This suggests 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.

Looking at the consumer substitution and the effects on CO_2 produced per car, the subsidy to filling stations have higher effects. 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 article 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. The AF that I consider, CNG and LPG, have market share big enough to credibly estimate the model, some of the takeaway of the analysis could be extended to other AF that share the same characteristics.

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 and prices 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

Ackerberg, D. A. and G. Gowrisankaran (2006). Quantifying Equilibrium Network Externalities in the ACH Banking Industry. *RAND Journal of Economics 37*(3), 738–761.

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

Allcott, H. and N. Wozny (2014). Gasoline Prices, Fuel Economy, and the Energy Paradox. *Review of Economics and Statistics 96*(5), 779–795.

Austin, D. and T. Dinan (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.

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

Berry, S. T. (1994). Estimating Discrete-Choice Models of Product Differentiation. *RAND Journal of Economics*, 242–262.

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

Björnerstedt, J. and F. Verboven (2016). Does Merger Simulation Work? Evidence from the Swedish Analgesics Market. *American Economic Journal: Applied Economics 8*(3), 125–164.

Bresnahan, T. F. and P. C. Reiss (1991). Entry and Competition in Concentrated Markets. *Journal of Political Economy 99*(5), 977–1009.

Busse, M. R., C. R. Knittel, and F. Zettelmeyer (2013). Are Consumers Myopic? Evidence from New and Used Car Purchases. *American Economic Review 103*(1), 220–256.

Eizenberg, A. (2014). Upstream Innovation and Product Variety in the US Home PC Market. *Review of Economic Studies 81*(3), 1003–1045.

Ferrari, S., F. Verboven, and H. Degryse (2010). Investment and Usage of New Technologies: Evidence from Shares ATM Network. *American Economic Review 100*(3).

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

Goldberg, P. K. and F. Verboven (2001). The Evolution of Price Dispersion in the European Car Market. *Review of Economic Studies 68*(4), 811–848.

Grigolon, L., N. Leheyda, and F. Verboven (2016). Scrapping Subsidies During the Financial CrisisEvidence from Europe. *International Journal of Industrial Organization 44*, 41–59.

Grigolon, L., M. Reynaert, and F. Verboven (2017). Consumer Valuation of Fuel Costs and the Effectiveness of Tax Policy: Evidence from the European Car Market. *American Economic Journal: Economic Policy*.

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

Huse, C. and C. Lucinda (2014). The Market Impact and the Cost of Environmental Policy: Evidence from the Swedish Green car Rebate. *The Economic Journal 124*(578), F393–F419.

Jacobsen, M. R. (2013). Evaluating US Fuel Economy Standards in a Model with Producer and Household Heterogeneity. *American Economic Journal: Economic Policy 5*(2), 148–187.

Katz, M. L. and C. Shapiro (1994). Systems Competition and Network Effects. *Journal of Economic Perspectives 8*(2), 93–115.

Kolesar, P. and E. H. Blum (1973). Square root laws for fire engine response distances. *Management Science 19*(12), 1368–1378.

Langer, A. and S. McRae (2013). Fueling Alternatives: Evidence from Naturalistic Driving Data. Technical report, Working paper.

Li, S., L. Tong, J. Xing, and Y. Zhou (2017). The Market for Electric Vehicles: Indirect Network Effects and Policy Design. *Journal of the Association of Environmental and Resource Economists 4*(1), 89–133.

McFadden, D. et al. (1973). Conditional Logit Analysis of Qualitative Choice Behavior.

Nurski, L. and F. Verboven (2014). Incumbency Advantages, Distribution Networks and ExclusivityEvidence from the European Car Markets. *International Journal of Industrial Organization 34*, 75–79.

Pavan, G., A. Pozzi, and G. Rovigatti (2017). Strategic Entry and Potential Competition: Evidence from Compressed Gas Fuel Retail. *CEPR Discussion paper 12113*.

Reguant, M. (2016). Bounding Outcomes in Counterfactual Analysis. *Working Paper*.

Reynaert, M. (2017). Abatement Strategies and the Cost of Environmental Regulation: Emission Standards on the European Automobile Market. *Working paper*.

Rysman, M. and J. Wright (2014). The Economics of Payment Cards. *Review of Network Economics 13*(3), 303–353.

Schiraldi, P. (2011). Automobile Replacement: a Dynamic Structural Approach. *RAND Journal of Economics 42*(2), 266–291.

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

Springel, K. (2017). Essays in Industrial Organization and Environmental Economics.

Train, K. E. and C. Winston (2007). Vehicle Choice Behavior and the Declining Market Share of US Automakers. *International Economic Review 48*(4), 1469–1496.

Verboven, F. (1996). International Price Discrimination in the European Car Market. *RAND Journal of Economics*, 240–268.

Tables

Table 1: Summary statistics - Demand

VARIABLES	LPG	CNG	DIESEL	GASOLINE
price (thousands of €)	16.60	20.00	25.44	16.49
	(4.62)	(6.43)	(10.13)	(6.94)
power/weight (kw/kg)	0.058	0.056	0.062	0.063
	(0.009)	(0.008)	(0.013)	(0.016)
fuel cost (€/100 km)	6.18	4.46	8.53	10.29
	(0.91)	(1.04)	(1.74)	(1.85)
length (l)	405.02	413.99	432.52	398.31
	(29.62)	(41.81)	(32.79)	(35.44)
CO_2 emissions (g/km)	127.29	118.53	128.88	131.65
	(17.84)	(17.04)	(26.01)	(23.21)
filling stations (N_j)	9.09	3.19	65.01	74.20
	(12.69)	(4.11)	(123.72)	(141.99)
$\log(N_j/M)$	-4.32	-5.04	-2.63	-2.57
	(0.82)	(0.81)	(0.81)	(0.82)
$\sqrt{M/N_j}$	4.73	6.74	2.02	1.97
	(2.08)	(2.78)	(0.84)	(0.85)
N. of observations	12233	1	3206	1
N. of observations	80202	1	45359	1
N. of models	46	10	193	174
N. of sales	104807	46293	389837	302688
N. of markets	570	487	572	572

Note: The table reports summary statistics of car characteristics sold in 2012 (standard deviations in brackets). The table presents vehicle characteristics that are sales weighted over the 572 markets in 2012 by fuel type. Price includes local taxes. M is the surface of the market measured in square kilometers.

Table 2: Summary statistics - Entry

VARIABLES	LPG	CNG
price fuel	0.83	0.98
	(0.02)	(0.03)
fuel sold per car	1326.38	1493.69
	(807.22)	(373.32)
pumps	5.37	1.73
	(8.93)	(3.09)
stock cars	3131.59	1266.54
	(8911.25)	(2956.79)
variable profit	70405.79	111768.71
	(60926.81)	(129756.94)
population	97164.87	99335.07
	(197275.78)	(201111.78)
cost shifters	92.05	1.32
	(51.65)	(2.67)
Observations	572	543

Note: The table reports summary statistics on market level determinants of variable profits and cost shifers (log of refinery distance in case of LPG and to log of numbers of connections to the pipeline in case of CNG). The price of fuel is in €/liter for LPG and €/kilogram for CNG. Standard deviations in brackets.

Table 3: Demand Results

	IV 2Nested Logit	IV 2NL instrument density
	(1)	(2)
Price (thousands of €)	-0.0180***	-0.0126***
	(0.0029)	(0.0028)
$\log(N/M) * AF$	0.372***	0.646***
	(0.00630)	(0.0231)
$\log(N/M)$	0.0341***	-0.0145***
	(0.0026)	(0.0049)
Power/weight (kw/kg)	2.488***	1.533***
	(0.473)	(0.455)
fuel cost (€/100 km)	-0.0049*	-0.0072***
	(0.0025)	(0.0025)
length (cm)	0.00163***	0.00106***
	(0.00029)	(0.00028)
σ_1	0.917***	0.910***
	(0.003)	(0.003)
σ_2	0.832***	0.835***
	(0.007)	(0.007)
implied price elasticity	-4.42	-2.85
N	141000	141000

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: In column (1) price and within group market share are instrumented, while in column (2) also AF density is instrumented. Fuels, model and region fixed effects as well as market characteristics (population density, average income and altitude zone) are included.

Table 4: Entry Results

VARIABLES	LPG	CNG
constant	7.39	7.20
	(0.40)	(0.56)
ln(pop)	0.33	0.35
	(0.03)	(0.05)
mandatoryAF	0.13	0.04
	(0.06)	(0.09)
north-east	-0.16	0.48
	(0.09)	(0.11)
center	-0.07	0.84
	(0.09)	(0.11)
south	-0.14	0.29
	(0.09)	(0.11)
islands	-0.25	-0.27
	(0.09)	(0.16)
cost shifter	-0.03	0.05
	(0.04)	(0.07)
ω	0.60	0.63
	(0.02)	(0.03)
Observations	572	543

Note: The table reports the coefficients of the ordered probit estimated through maximum likelihood. I am not reporting the marginal effects, since I am only interested in coefficients' signs. Cost shifter refers to log of refinery distance in case of LPG and to log of numbers of connections to the pipeline in case of CNG.

Table 5: LPG policy comparison.

	Price Rebate			Filling station subsidy		
	Avg (% Δ)	5^{th} percentile (%Δ)	95^{th} percentile (% Δ)	Avg (% Δ)	5^{th} percentile (%Δ)	95^{th} percentile (% Δ)
			Direct effect			
			Car purchases			
Subsidized	**2.28**	**0.00**	**0.00**			
Others	-0.05	0.00	0.00			
			Pump density			
				89.56	0.00	173.66
			Overall effect			
			Car purchases			
Subsidized	**2.26**	**0.00**	**6.17**	**47.67**	**34.99**	**48.47**
Others	-0.05	0.00	0.00	-1.22	-0.25	-1.70
			Pump density			
	0.12	0.00	0.00	111.23	0.00	251.97

Note: The left table reports the effects of 1,700€ price reduction of LPG cars. 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 overall LPG market share variation was equal respectively to the 5^th and 95^th percentile.

The right table reports the effects of a 60% 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 overall LPG pump density variation was equal respectively to the 5^th and 95^th percentile.

Results are average from 100 simulations of the model.

Table 6: CNG policy comparison

	Price Rebate			Filling station subsidy		
	Avg (% Δ)	5^{th} percentile (%Δ)	95^{th} percentile (% Δ)	Avg (% Δ)	5^{th} percentile (%Δ)	95^{th} percentile (% Δ)
			Direct effect			
			Car purchases			
Subsidized	**1.92**	**0.00**	**1.82**			
Others	-0.03	0.00	-0.07			
			Pump density			
				59.69	0.00	188.76
			Overall effect			
			Car purchases			
Subsidized	**2.15**	**0.00**	**6.31**	**34.32**	**0.00**	**66.92**
Others	-0.03	0.00	-0.08	-0.55	-0.00	-0.78
			Pump density			
	0.80	-2.51	14.81	80.74	0.00	288.12

Note: The left table reports the effects of $1,700$€ price reduction of CNG cars. 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 CNG market share variation was equal respectively to the 5^th and 95^th percentile.
The right table reports the effects of a 60% 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 overall 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 7: CO2 comparison

	LPG (g/km)	CNG (g/km)
	Average CO2 per car	
Price Subsidy	0	0
Filling Station Subsidy	-0.22	-0.3

Note: The table reports the average reduction of CO2 per car under the four different policy scenatios: price rebate for LPG/CNG, filling station subsidies for installing LPG/CNG pumps.

Table 8: Setting filling station standard.

Average AF pump density

	Avg Δ (%)	MinΔ (%)	MaxΔ (%)
LPG	31.29	-2.44	300.00
CNG	25.92	0.00	283.33
Traditional fuels	-0.16	-2.02	0.00

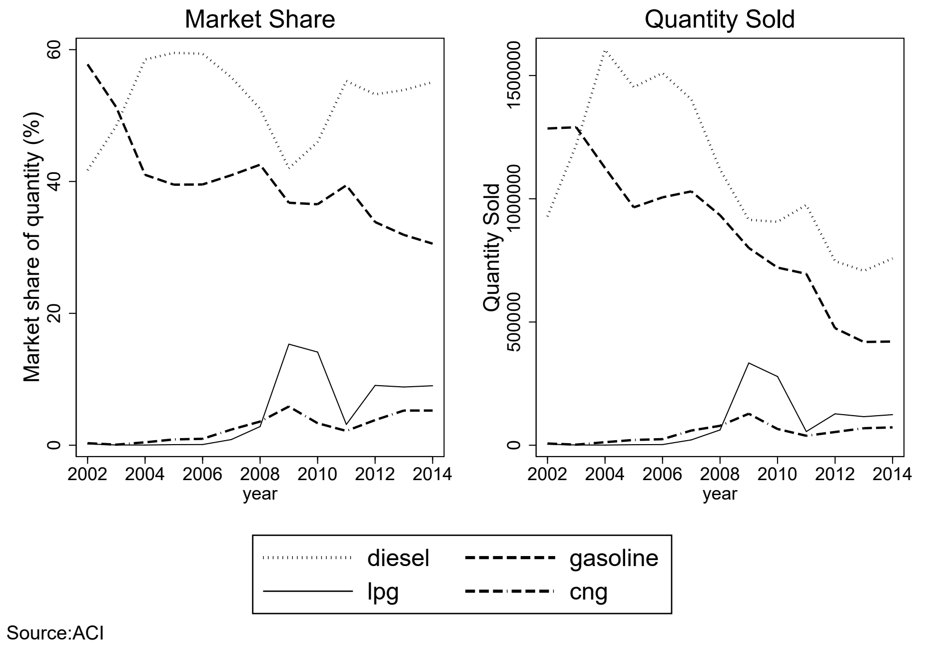
Traditional fuel pump density

	Avg Δ (%)	MinΔ (%)	MaxΔ (%)
LPG	194.02	0.00	719.44
CNG	353.14	0.00	1512.41
Traditional fuels	-3.65	-14.80	0.00

Note: The left table reports the variation in market composition implied by setting the pump density of AF filling stations to at least the average AF pump density. The right table reports the variation in market composition implied by increasing AF pump density at the TF filling station one (each existing traditional fuel filling station add the extra pump of CNG and LPG).
Results are average from 100 simulations of the model.

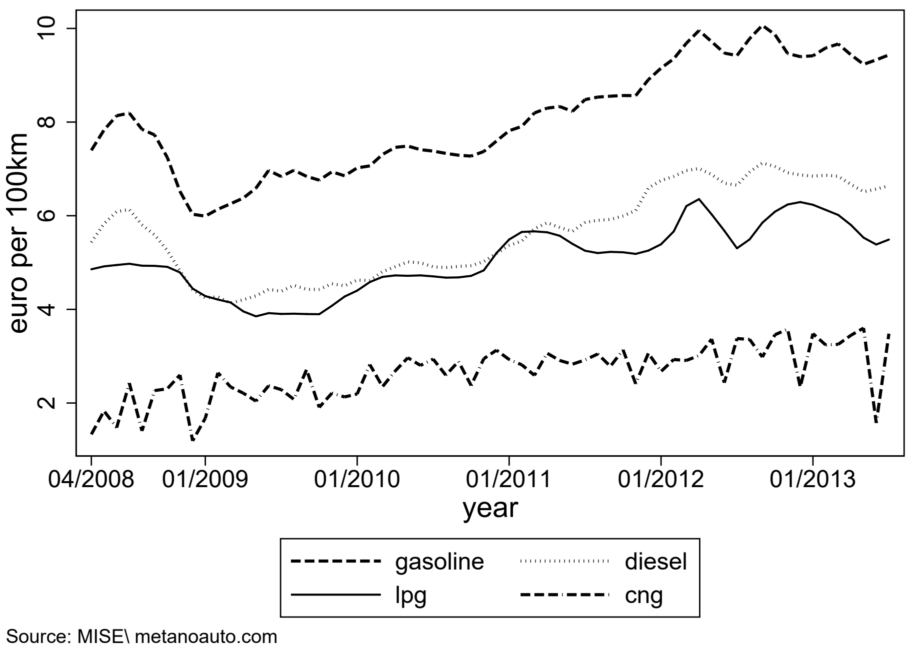
Figures

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



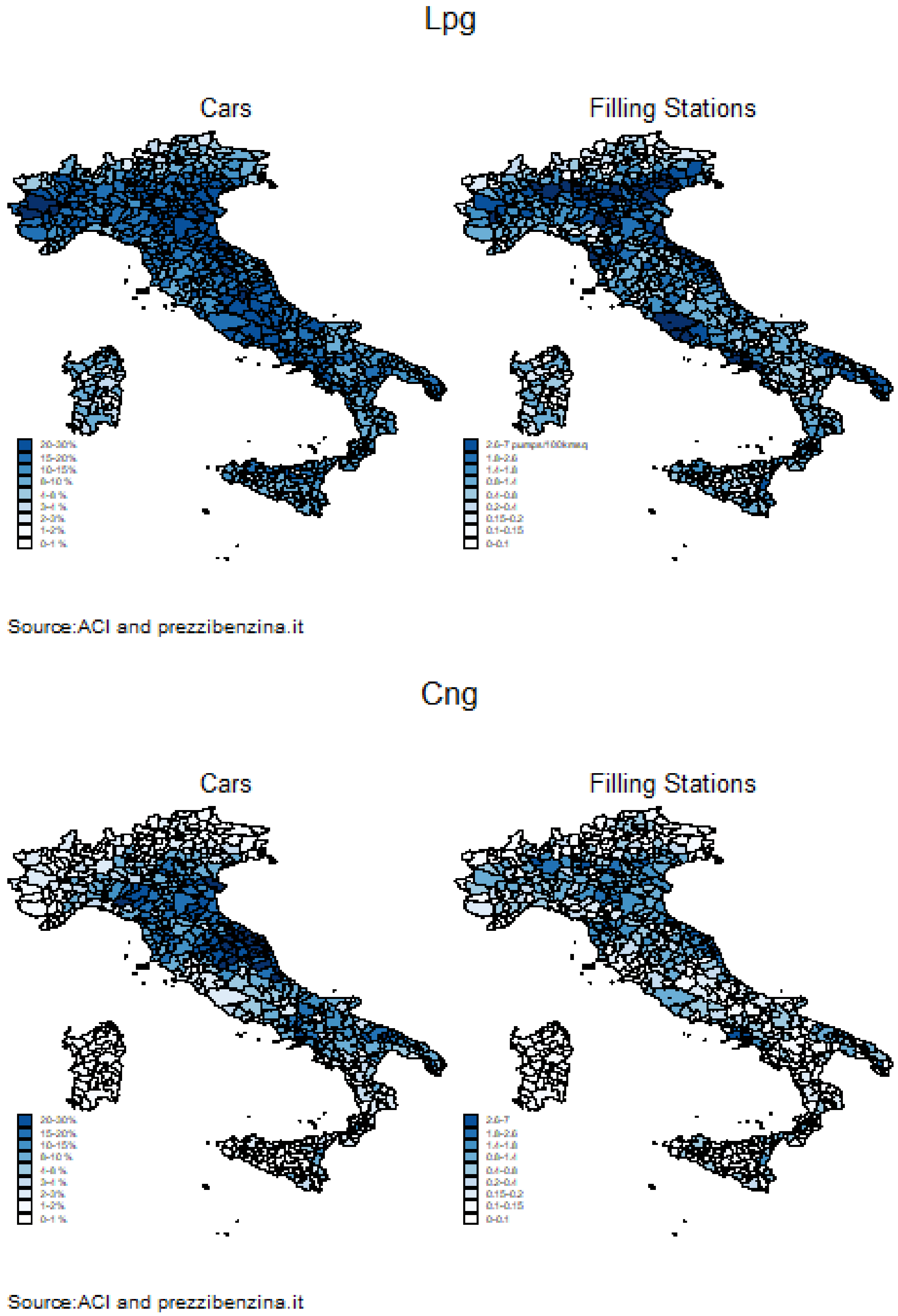
Note: The figure shows the market trend by fuel in Italy from 2002 to 2014. The left panel plots the share of cars by fuel type. The right panel plots the quantity of cars in levels.

Figure 2: Fuel price per 100 km



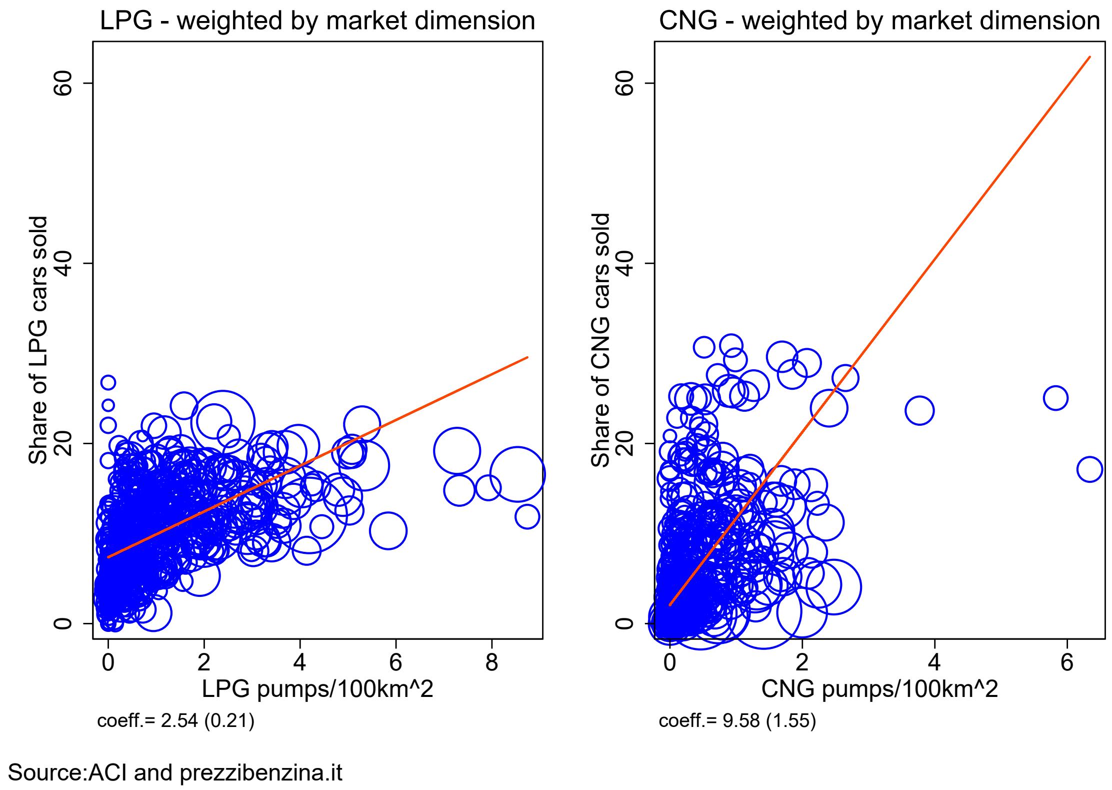
Note: The figure plots the fuel cost for running 100km from 2008 until 2013. Fuel costs are computed using the average fuel efficiency for "compact" cars (as reported in the specialized magazine "Quattroruote" September 2012).
Gasoline and diesel price often move together and diesel cars are more than 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.



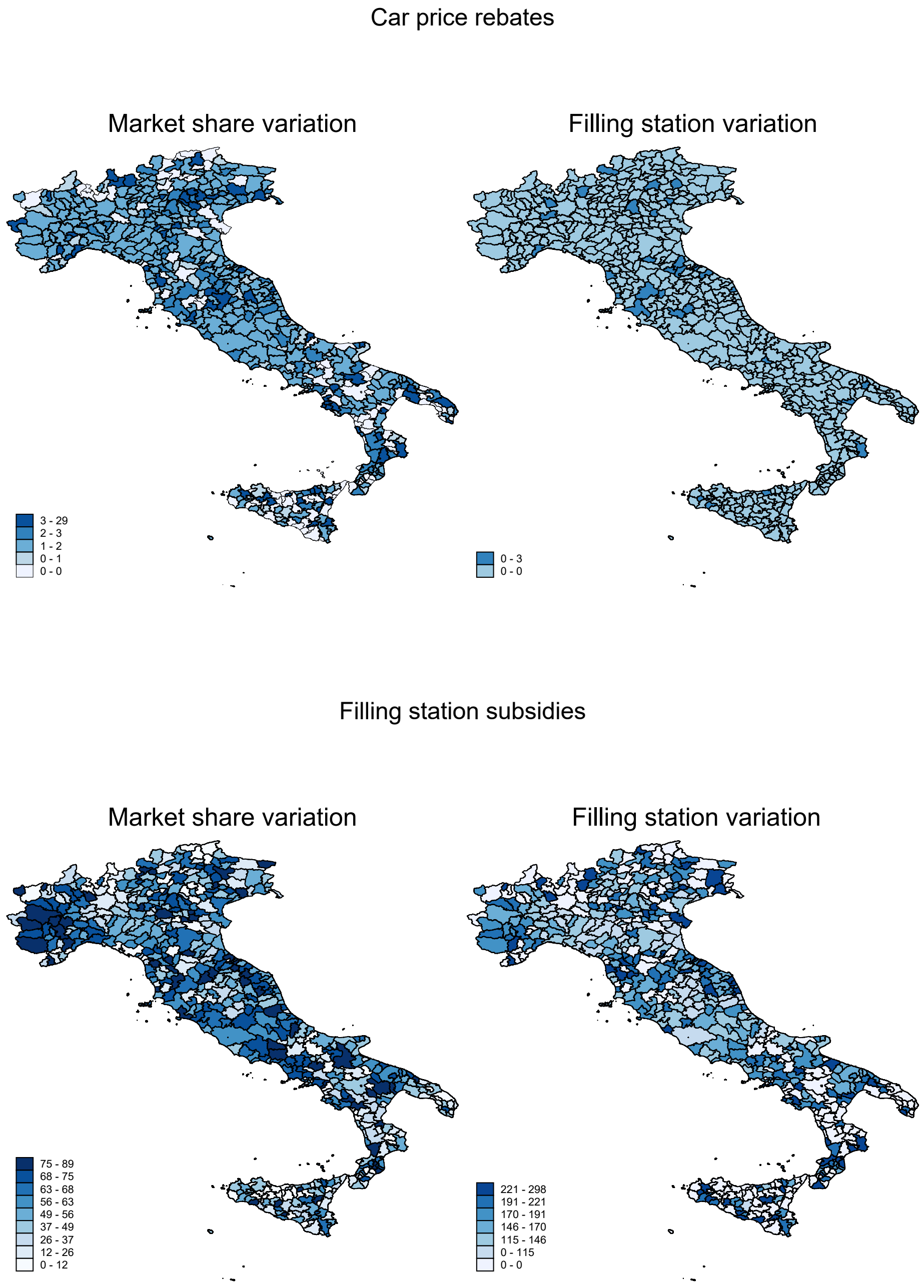
Note: The figure shows Italian LMA share of AF cars and filling station density in 2012. The upper maps refer to LPG (autogas) cars and filling station density, the lower maps refer to CNG (natural gas) cars and filling station density. The maps on the left refer to the market share at market level, 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



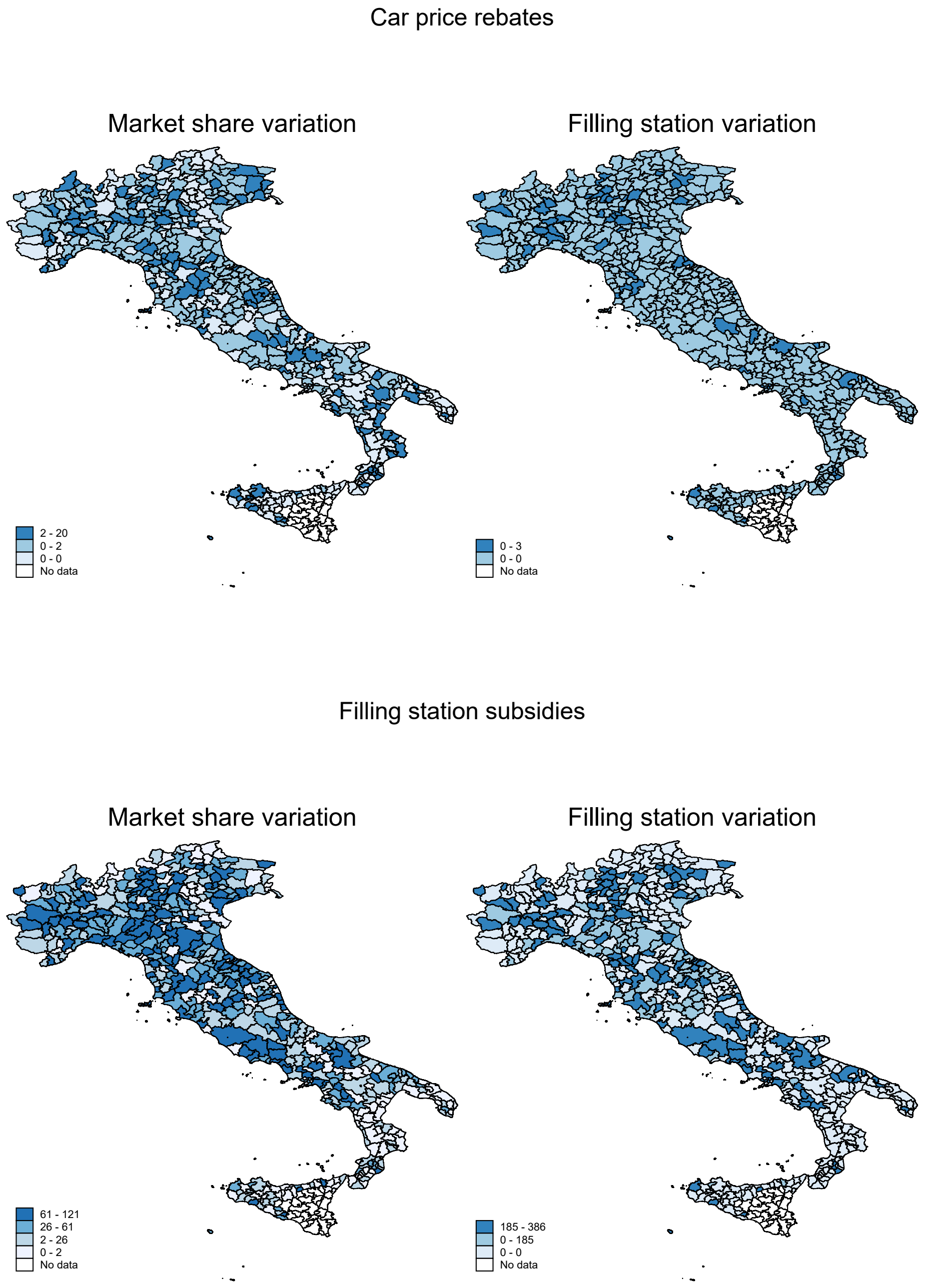
Note: The panels report scatterplots between the share of AF cars sold in 2012 and the AF filling stations' density. Each dot refers to a LMA and its dimension is proportional to market dimension. The line refers to the slope of a weighted regression of the share of AF cars on the AF filling stations' density.
The left panel refers to LPG (autogas) cars, the right one refers to CNG (natural gas) cars.

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 subsidies 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 subsidies 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.

Appendix - Not for publication

A 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.

$$\mathcal{L}(\theta) = \sum ln \left(\Phi \left(\frac{ln(VP_m(n_m)) - \gamma W_m}{\omega} \right) - \Phi \left(\frac{ln(VP_m(n+1)) - \gamma W_m}{\omega} \right) \right). \tag{12}$$

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

$$\begin{aligned} \mathcal{L}(\theta) = \sum_m ln & \left(\Phi \left(\frac{ln((p_m - mc_i)k\frac{1}{n_m}(\hat{q}_m(n_m) + Q_m)) - \gamma W_m}{\omega} \right) \right. \\ & \left. - \Phi \left(\frac{ln((p_m - mc_i)k\frac{1}{n_m+1}(\hat{q}_m(n_m+1) + Q_m))) - \gamma W_m}{\omega} \right) \right). \end{aligned} \tag{13}$$

Consider the number of sold cars q_{mf} in a market m with a given fuel f. As I consider a nested logit, following Berry (1994) and Verboven (1996), I can compute the market share as:

$$\begin{aligned} s_{jm} &= \frac{e^{\delta_{jm}/(1-\sigma_1)}}{e^{I_{sfm}/(1-\sigma_1)}} \frac{e^{I_{sfm}/(1-\sigma_2)}}{e^{I_{fm}/(1-\sigma_2)}} \frac{e^{I_{fm}}}{\sum_{f=0}^{F_m} e^{I_{fm}}} \\ I_{sf} &= (1-\sigma_1) ln \sum_{j=1}^{Jsf} exp(\delta_j/(1-\sigma_1)) \\ I_g &= (1-\sigma_2) ln \sum_{s}^{S_f} exp(I_s f/(1-\sigma_2)) \\ I &= ln(1 + \sum_{f=1}^{F} exp(I_f)) \end{aligned} \tag{14}$$

where the mean utility is $\delta_{jm} = \alpha p_{jm} + x_j\beta + n_{jm}\lambda + \xi_{jm}$ and the quantity of cars using a given fuel is:

$$q_{mf} = \sum_{j \in \mathcal{C}_f} s_{jm} L_m. \tag{15}$$

Using equation (13) and (15) I get the likelihood I maximize to estimate γ.

$$\begin{aligned}\mathcal{L}(\theta) = \sum_m ln \Bigg(\Phi \left(\frac{ln\left((p_m - mc_i)k\frac{1}{n_m}(\sum_{j \in \mathcal{C}_f} \hat{s}_j(n_m) + Q_m)\right) - \gamma W_m}{\omega} \right) \\ - \Phi \left(\frac{ln\left((p_m - mc_i)k\frac{1}{n_m+1}(\sum_{j \in \mathcal{C}_f} \hat{s}_j(n_m+1) + Q_m)\right) - \gamma W_m}{\omega} \right) \Bigg).\end{aligned} \tag{16}$$

B Robustness check

In this section I explore the robustness of my results in demand estimation, considering a different definition of availability. If consumers value the distance to the nearest retailer and not their density, we should change our demand specification. Assuming that consumer and retailers follow a spatial Poisson process, following Kolesar and Blum (1973) it is possible to derive the nearest retailer distance as $d(N) = 0.5\sqrt{M/N}$. Ferrari et al. (2010) use this definition for ATM demand and Nurski and Verboven (2014) apply to cars' dealer distance.

[Table 9 about here.]

Tables

Table 9: Demand Robustness check.

	IV 2Nested Logit	IV 2NL instrument distance
	(1)	(2)
Price (thousands of €)	-0.0191***	-0.0122***
	(0.003)	(0.003)
$0.5\sqrt{M/N} * AF$	-0.0962***	-0.308***
	(0.00373)	(0.0143)
$0.5\sqrt{M/N}$	-0.0625***	0.133***
	(0.00352)	(0.0133)
Power/weight (kw/kg)	2.580***	0.978**
	(0.480)	(0.466)
fuel cost (€/100 km)	-0.00436*	-0.00929***
	(0.00258)	(0.00251)
length (cm)	0.00172***	0.000937***
	(0.000295)	(0.000287)
σ_1	0.914***	0.888***
	(0.00294)	(0.00352)
σ_2	0.828***	0.805***
	(0.00682)	(0.00765)
implied price elasticity	-4.54	-2.22
N	141000	141000

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: In column (1) price and within group market share are instrumented, while in column (2) also AF distance is instrumented.Fuels, model and region fixed effects as well as market characteristics (population density, average income and altitude zone) are included.