Sustainability Environmental Economics and Dynamics Studies

Working Paper Series

Between and within vehicle models hedonic analyses of environmental attributes: the case of the Italian used-car market

by

Giuliano Rolle

08/2022

SEEDS Working Paper 08/2022
August 2022
By Giuliano Rolle

Between and within vehicle models hedonic analyses of environmental attributes: the case of the Italian used-car market

Giuliano Rolle

Università degli Studi di Ferrara

giulianomarcof.rolle@edu.unife.it

Abstract

To achieve carbon neutrality by 2050, the transportation sector must radically reduce its greenhouse gas emissions (GHGEs) emissions. According to earlier research, a growth of the market share of the used car market and an expansion of the lifetime of second-hand vehicles can play a crucial role in preventing a considerable amount of carbon dioxide (CO_2) emissions.

So, the purpose of this paper is to estimate, through a series of hedonic pricing models (HPMs), the consumers' marginal willingness to pay (MWTP) for three environmental attributes of used cars: their level of fuel efficiency, their level of CO_2 emissions, and their belonging to one of the European emission categories. To perform this analysis, two original cross-sectional datasets (the Panda and the Milan ones) were created through a scraping process of the used cars' listings contained in the Italian version of the AutoScout24's online advertising platform.

Despite its several limitations, the implications that can be derived from this work, which has estimated a relevant consumers' MWTP for vehicles that have an improved fuel efficiency - especially in the Milan HPMs - and that comply with the highest European emission standards, and a very small or even negative MWTP for cars' with a reduced level of CO_2 emissions, is a support for higher investments in policies that will encourage the purchases of used cars with a high degree of these environmental features and, at the same time, the dismantling of the oldest and most polluting vehicles of the national fleet.

1. Introduction

At the global level, the transport sector produced about 8.9 gigatons (Gt) of carbon dioxide equivalent (CO2eq) in 2019, a rising figure compared to the one of 5.1 Gt CO2eq of 1990. Between the various sectors, transport was the fourth-largest contributor of greenhouse gases at the international level in 2019 (Teter, 2020).

Furthermore, the transportation sector was responsible for 25.2% of total Italian 2019 GHGEs, of which 92.6% came from road transport. From 1990 to 2019, GHGEs from road transportation increased by 3.9%. The preponderance of emissions from transport by road highlights the criticality of the Italian transport system as a whole (ISPRA, 2019).

While accounting for the highest level of transport CO_2 emissions, passenger cars and freight offer, at the same time, the greatest decarbonization opportunities (Taptich et al., 2016; Halim et al., 2018). There are several approaches for reducing transportation emissions, and they can be classified using the "Avoid-Shift-Improve" (ASI) framework (Taptich et al., 2016). For instance, "Improve" solutions try to decrease transport's emissions per kilometre and consists of incentives for hybrid and electric cars, greener fuels with lower carbon emissions, scrappage programmes for vehicle with a high level of harmful emissions, and anti-idling and ecological driving campaigns (Lutsey & Sperling, 2012; Gota et al., 2015).

Furthermore, the fuel efficiency of new Internal Combustion Engine (ICE) cars, has, on average, increased dramatically over recent years, thanks mostly to stricter pollution standards. Nevertheless, progress has slowed recently (GFEI, 2020).

Accelerating the transition to a more sustainable and smart mobility, with a view to achieving climate neutrality by 2050, is among the ambitious goals set out in the European Green Deal of 2019: a 90% reduction in emissions from transport is, indeed, required by 2050, compared to the 1990 levels. The objective of sustainability in transport is part of the new inclusive growth strategy aimed at transforming the EU into an equitable, prosperous society with a modern, efficient and competitive economy, in which the growth of this latter is decoupled from its resource use and environmental impact (ISPRA, 2019; Wolf et al., 2021).

At first sight, the second-hand car market plays an unclear role regarding this objective: in fact, as shown by Nakamoto (2017), increasing the sales of used cars, which have a relatively poorer fuel efficiency compared to the one of new cars, fosters the average CO_2 emissions in the driving phase of the national car fleet, while, at the same time, it avoids the emissions generated by the unneeded additional manufacturing phases. Thus, when considering cars' entire life cycle, it is not trivial what kind of net impact an increase in the market-share of the used automobiles can have on the transportation sector' total emissions (Nakamoto, 2017).
Nakamoto (2017) thoroughly investigated this with an LCA study of the Japanese fleet and found that a combined strategy of extending vehicles' lifetimes - after having established a target age for used automobiles - and expanding the market share of used cars can help achieve a low-emission transport sector.

In addition, the secondary auto market has become increasingly important in recent years, due to the issues that are putting the European and Italian car manufacturers and the related automobiles' primary market in a severe downturn, which has arisen, specifically, due to the COVID-19 pandemic, the subsequent supply-demand crisis and the destruction of the global value chains of the car and its associated sectors, like the microchip one (Wu et al., 2021).

In Italy, compared to the 2020 level, there was a recovery in the number of sold used cars, thanks to 4.96 million changes of ownership in 2021. The comparison of this second-hand market figure with the 2021 number of sales of new personal vehicles (1.46 million) further emphasizes the importance and relevance of the Italian used car market (UNRAE, 2021).

So, the objective of this paper is to evaluate, by means of the HPMs of Chapter 4, the partial elasticity (and semi-elasticity) of the price of the considered used cars in relation to their fuel efficiency level, their level of CO_2 emissions, and their belonging to one of the European emission categories, in order to understand if there is a marginal willingness to pay for enhanced level of these cars' environmental related attributes.

As stressed out by Galarraga et al. (2014), in a context of constant policy developments in the transportation sector, which are needed to cope with the present and future challenges posed by climate change, it is crucial to understand how relevant cars' fuel economy and other environmental-related factors are for drivers when purchasing second-hand automobiles.

Furthermore, the employed statistical observations (namely the data of the considered used cars) were derived from two original datasets, created through a scrapping process of the Italian version of the online advertising platform of AutoScout24. More specifically, the following two cross-sectional datasets were studied, in order to partially cope with the problem of market segmentation and to have more robust findings from different perspectives: one containing as observations the data of all the AutoScout24's listings of a very popular Italian A-segment car (EEC, 1999), namely the Fiat Panda, at the Italian level, and the other one containing as statistical units the data of the listings of all the different vehicles sold in the platform within the boundaries of the Metropolitan City of Milan. The vehicles considered in both these two data frames have a first registration year between 2010 and 2020 and have a gasoline or diesel engine.

The remainder of this paper is structured as follows: Chapter 2 presents the methodological and theoretical background behind this work; Chapter 3 illustrates the data collection process, the variables' description and their descriptive statistics; Chapter 4 shows the used hedonic models and their estimated results and, eventually, Chapter 5 draws the conclusions of this work.

2. Theoretical background

2.1 The Hedonic Pricing Method

People's observable behaviours and consumption choices are used by revealed preference methods to indirectly (or directly) infer the use value of non-market assets (Tietenberg & Lewis, 2019; Pearce et al., 2006). Some of the factors that go into the determination of the price of a vehicle are not independently priced and/or are not negotiated independently in the car market. One example of this is car brands, which, although they do not have a distinct price, actually, influence the price of automobiles (Hadinejad & Shabgard, 2011). In particular, the hedonic pricing method, which is a revealed preference methodology, can be used to calculate, ceteris paribus, the marginal WTP of discrete changes in a studied characteristic of the considered good (Tietenberg & Lewis, 2019).

Initially, the hedonic pricing method was born as an experimental approach for adjusting price indices of commodities in response to changes of their characteristics. Subsequently, Lancaster's consumer theory of 1966 and Rosen's one of 1974 developed the theoretical foundations of the hedonic pricing method, sustaining that a good is a bundle of numerous separate features, whose combination impacts the individuals' desire for it (Lancaster, 1966; Rosen, 1974; Hadinejad & Shabgard, 2011). The theories of both Lancaster and Rosen tries to derive the prices of the features of the considered good by studying the nexus between the reported prices of the various versions of the given product and the characteristics associated with each version (Chau & Chin, 2003).

The Lancaster's and Rosen's models differ because of the following relevant discrepancies: the Lancastrian theory assumes that every commodity is a member of a wider group of products, and that, in each group, all the goods (or at least some) are alongside consumed, respecting the given individual's budget constraint. On the other hand, also Rosen's model presumes that there is a range of products, but, according to him, individuals do not purchase their preferred features by acquiring a combination of commodities. Indeed, according to Rosen, each product is selected from the spectrum of the various alternatives and is consumed separately. Because of this difference between their models, Lancaster's theory is more suitable for consumer goods, while Rosen's one for durable goods, such as cars (Chau & Chin, 2003).

Moreover, Lancaster presumes a linear relation between the characteristics embedded in the products and their price. Additionally, implicit prices are steady over ranges of features levels; they can only vary when there is a modification in the bundle of commodities consumed.
On the other hand, Rosen assumes that a nonlinear relation between the contained features of the products and their price would be most likely, unless it is feasible for individuals to choose features by unbinding and recomposing them. This non-linearity entails that the implicit prices are not steady but vary in relation with the level and quantity of the characteristics being purchased, and regarding the number of other features connected with the product and to the given functional form of the equation defining the hedonic function (Chau & Chin, 2003).

Finally, both the Lancaster (1966) and the Griliches (1961) approaches affirm that the prices of automobiles reflect the economic evaluation of the features that are embodied in the various models of cars. Based on this, the hedonic pricing method assumes that the differences in the prices of the automobiles are attributable to the magnitude and qualities of their characteristics (Hadinejad & Shabgard, 2011).

2.2 Hedonic Pricing Method and WTP for environmental improvements in vehicles

The idea for which customers underestimate the energy efficiency of their cars was the subject of a long debate and is used as a reason in support of the implementation of environmental standards (Allcott & Wozny, 2013).

Consumers' preferences for cleaner automobiles can be evaluated through the customers' revealed preferences, and, in particular, the hedonic pricing method (Liu and Helfand, 2012).

More specifically, there is an early series of publications (Kahn, 1986; Atkinson & Halvorsen, 1984; Goodman, 1983) that employed the hedonic pricing method to examine the impact of gasoline price rises on customers' choices for energy-efficient automobiles during the oil crises of the seventies (Galarraga et al., 2014). These publications focused mostly on the US car market and found a variety of outcomes: for instance, Goodman (1983) discovered, with his dataset composed of the information about the characteristics of two-years old cars sold between 1977 and 1979 in the USA, that the WTP for improved fuel economy decreases by about 2% for each 1% growth in fuel efficiency.

Furthermore, according to Alberini et al. (2016), because of the strong collinearity between car features and fuel efficiency (Atkinson & Halvorsen, 1984; Knittel, 2011) and the issue of misspecification, the first generation of empirical studies regarding the fuel efficiency premium based on the hedonic pricing method was characterized by various limitations and produced contradictory findings about the MWTP for fuel economy (Goodman, 1983; Arguea & Hsiao, 1993; Witt, 1997).

Theoretically, if people do not gain utility from their automobiles' fuel efficiency and this latter is present in their utility optimisation issue only through the limits imposed by their budget, customers should assign identical importance to their hedonic price of fuel efficiency and the discounted flow of future fuel expenses (Alberini et al., 2014). So, the hedonic pricing method approach was used by Chugh et al. (2011) to verify this hypothesis, by using the data of four different segments of the Indian car market. To cope with the issue of correlation with unobservable factors, these authors used the instrumental variables technique with mean fuel efficiency of the same vehicle brand and body type as the instrument for fuel economy. In the model specifications, in which they were able to reject the above-mentioned hypothesis, they found that consumers were overvaluing cars' fuel efficiency.

On the other hand, Espey and Nair (2005) elaborated several models to verify the same hypothesis of Chugh et al. (2011), employing vehicles' data from the 2001 US primary car market. Although their findings agree with those of Chugh et al. (2011), discovering that the WTP for more fuel-efficient automobiles is higher than the related fuel savings, they argued that drivers actually were making rational decisions when doing so, since this "contradiction" can be explained by customers' concerns for the environment.

In contrast to Espey and Nair (2005) and Chugh et al. (2011), Allcott and Wozny (2013) showed that only around 70% of future gasoline costs are absorbed in the cost of a vehicle under credible assumptions about discount rates and consumer expectations of future fuel prices.

Consumers' inability to foresee future gasoline prices is considered as evidence in support of regulatory measures, which, for some authors, should be preferred over market-based policies (West and Williams, 2005; Bento et al., 2009; Anderson et al., 2020).

Furthermore, also environmental labelling schemes play a crucial role: their objective is to give trustworthy information to customers about the environmental impacts of goods and services, thanks to reliable predetermined reference standards. They are a relatively cheap and often easy-to-implement policies for addressing the issues of information asymmetry and market failure, by favouring the pro-environment decisions of consumers (Sammer & Wüstenhagen, 2006; Van Amstel et al., 2008).
Alberini et al. (2014) adopted a labelling system as a fuel efficiency proxy, in order to assess the Swiss customers' WTP for cars' fuel economy, their trade-off between new vehicle price and fuel cost savings during the entire car's lifespan, and to evaluate whether the Swiss automobile labels, which inform consumers about cars' main environmental characteristics, have an extra influence on cars‘ price, above and beyond the one of fuel efficiency alone. From a methodological perspective, the choice of employing the Swiss energy label for cars was made to address the issues of multicollinearity and misspecification. Alberini et al. (2014) discovered that cars in the top efficiency class categories (A-label) came with a 5% price premium, when compared to B-label automobiles, and that this price premium was larger than the discounted value of fuel cost reductions.

3. Methodological approach

3.1 Data Collection

The two original cross-sectional datasets (the Panda and the Milan ones) used for the hedonic analyses presented in this paper were obtained through a scraping process of the Italian version of the online advertising platform of AutoScout24. In this platform, listings of used, but also of new and zero kilometres cars, commercial vehicles, trailers, motorcycles and camper van are submitted by their users and promoted online in order to be sold (AutoScout24, 2020a).

In particular, AutoScout24 is the biggest European online platform for used vehicles, with over 30 million of monthly users (10 million in Italy), over 43,000 car retailer partners (8500 in Italy), an average of 1.5 million listings (20% of which are from Italian users), and around 500 employees (50 in Italy). (AutoScout24, 2020a, b).

More specifically, the web scraping programme was created using the Python programming language. Web scraping is generally recognised as an efficient and effective approach for gathering large amounts of heterogeneous information and data from internet sites (Zhao, 2017; Mooney et al. 2015; Bar-Ilan 2001). The method of scraping information from the web is made of two main steps: the acquisition of online data and the extraction of the needed information from the collected web resources (Zhao, 2017).

The Panda data frame comprises as observations all the AutoScout24's listings of a very popular Italian A-segment car (EEC, 1999), namely the Fiat Panda, at the Italian level, whereas the Milan dataset contains as statistical units the data of the listings of all the various vehicles sold in the platform within the boundaries of the Metropolitan City of Milan. The vehicles considered in both these two data frames have a first registration year between 2010 and 2020 and have a gasoline or diesel engine.

The scraping process was made from the 2nd of March 2022 to the 4th of March 2022 for the Panda dataset, whereas from the 29th of March 2022 to the 9th of April 2022 for the Milan one.

3.2 Dependent variable

The dependent variable of the hedonic models of Chapter 4 is the asking price (in euro) of the AutoScout24's listings of the considered second-hand cars.

The asking price reported in the considered second-hand car listings is assumed to represent the purchasing price. As a consequence, the analyses of this thesis are based, just like the Doležalová (2020)'s one, on the strong assumptions for which the sellers determined their price according to car features, adequate knowledge of the secondary market and an optimal pricing strategy.

3.3 Key independent variables

3.3.1 Cars' combined fuel consumption

The first studied explanatory variable is the manufacturer-measured combined fuel consumption (FUELCOMBO) of the considered cars, which was displayed in the AutoScout24's considered listings. It is measured in litres per 100 kilometres.

In addition, following the example of Alberini et al. (2014), in the hedonic analyses of this work, the top 5% of the distribution of FUELCOMBO (for instance, a value greater than 8.2 litres per 100 in Model M.3) were excluded. This achieves the objective of eliminating high performance, highly costly and high-status sporting automobiles, and vehicles with atypically high fuel consumption. Indeed, when buying one of these automobiles, fuel efficiency is unlikely to have a significant role (Alberini et al., 2014)

In theory, better fuel efficiency is expected to have a positive impact on the price of a vehicle from two different perspectives: reduced transportation costs and environmental impact (Doležalová, 2020; Kihm & Vance, 2016). For instance, the findings of Kihm and Vance (2016) indicates that a decrease of 1 litre of gasoline per 100 kilometres in the car's fuel economy raise the price of a car by €579 for new cars and by €813 for second-hand ones, everything else being equal.

However, it is also likely that the consumers' WTP for fuel efficiency has shifted over time, because of changing customer preferences (Murray & Sarantis, 1999; Matas & Raymond, 2009).

3.3.2 Vehicles' carbon dioxide emission level

The second studied explanatory variable is the one accounting for the carbon dioxide emission level (CO2) of the considered cars, which is measured in grams per kilometre.

To the best of the author's knowledge, in the literature of the hedonic pricing method applied to the car market, very few papers assessed the impact of the cars' exhaust gas level on their market price. One reason for this could be the difficult in disentangling the hedonic prices of fuel efficiency and pollution level, since they are highly correlated (Kuru, 2017).

Struggling to increasingly strict air quality regulations, several municipal and state governments in the United States have developed policy measures to control used-vehicle pollutants' level, such as car inspections and compulsory maintenance programmes, to minimise their pollution. So, the presence of mandatory car inspection and maintenance programmes may force the internalization of some of the negative externalities associated with driving a polluting-intensive car. Because of this, vehicles with lower emission may receive a market premium for their environmentally friendly characteristics, in the case in which the buyers of second-hand cars recognise such private costs of driving high-polluting automobiles (Bin & Martins-Filho, 2008).
Thus, Bin and Martins-Filho (2008) used a hedonic model with the cars' pollution level as one independent variable to test this hypothesis and determine the hedonic price of cars' hydrocarbon emissions. Their findings showed that a higher amount of pollutant emissions have a significant negative impact on the price of cars with an emission level below the average, but not on the price of high-polluting automobiles, which tendentially would fail the emission inspections.

Finally, according to Kuru (2017), consumers who give a value to the reduction of their car's negative impacts may be willing to pay for an altruistic contribution to the fight against climate change or for demonstrating their own environmentally friendly values.

3.3.3 European emission standards

The third and last studied explanatory variables is the categorical variable for the considered European emission classes. Directive 70/220/EEC of 1970 and its subsequent amendments provides the legal framework of the European emission standards for, among the others, light-duty (cars, vans) vehicles (Council Directive, 1970).

In the Panda HPMs were considered vehicles with a EURO 6D (including EURO 6D-TEMP), EURO 6, EURO 5, EURO 4 emission classes, while in the Milan HPMs were considered EURO 6 (also including EURO 6D and EURO 6D-TEMP), EURO 5 and EURO 4 emission categories.

Normally, in the primary market, the Euro Emission categories act as endorsement labels, as defined by Haq and Weiss (2016), underlying the fact that a given car satisfies the emission threshold of its specific emission category. On the other hand, in the secondary market, the Euro Emission categories function as a comparison label, again as illustrated by Haq and Weiss (2016), which enables customers to compare two similar cars for all the other attributes, by focusing on their different emission level of harmful pollutants.

Furthermore, similarly to the cars' CO_2 emission level, also these European emission categories (and, especially, the best ones) could signal the consumers' appreciation of a limited environmental negative impact of their cars, comprising the readiness to altruistically pay to contribute to the fight against climate change, along with the desire to indicate their own ecologically friendly personality.

Eventually, a MWTP for cars with the highest European emission classes could be explained, at least partially, by their guaranteed and lawful capability to have access to some city centres and their surrounding areas, like the ones of the city of Milan (Area B and Area C) or the ones of the majority of the other municipalities of the Metropolitan City of Milan. These no-go zones for pollution-intensive automobiles were created to enhance the city air quality. Currently, the following European emission classes are affected by the almost citywide Area B's traffic ban: Diesel-EURO 0, 1, 2, 3, and 4 and Gasoline-EURO 0 (Colantone et al., 2022, Regione Lombardia, 2022).

3.4 Other variables

To take into account the other factors influencing used cars' price, the following control variables of the considered used automobiles were included in the HPMs:

- Engine Displacement (CC), measured in cubic centimetres;
- Horsepower (HP), measured in horsepower;
- Age of the vehicle (YEAR);
- Type of fuel (FUEL);
- Type of gearbox (GEAR_TYPE);
- Types of transmission (TRANSMISSION_TYPE);
- Vehicles' external colour (COLOURS);
- Vehicles' brand and model (MODEL, only for the Milan Dataset).

3.5 Descriptive statistics: the Milan Dataset

The first cross-sectional dataset, the so-called Milan Dataset, was used in this work to develop a hedonic analysis to estimate the price elasticity (or semi-elasticity) of the considered used cars sold within the boundaries of the Metropolitan City of Milan in relation to their three studied variables. More specifically, it was used a series of subsets of the Milan data frame, each of them with a slightly different sample in terms of considered statistical units and their total number, because of the partial incompleteness of the data scraped from AutoScout24.

Table 1 shows the descriptive statistic of the level form of the quantitative variables employed in one of the main Milan hedonic models, namely in Model M.3, which almost reflects perfectly the distinctive characteristics of the observations used to assess the other HPMs of sections 4.2.

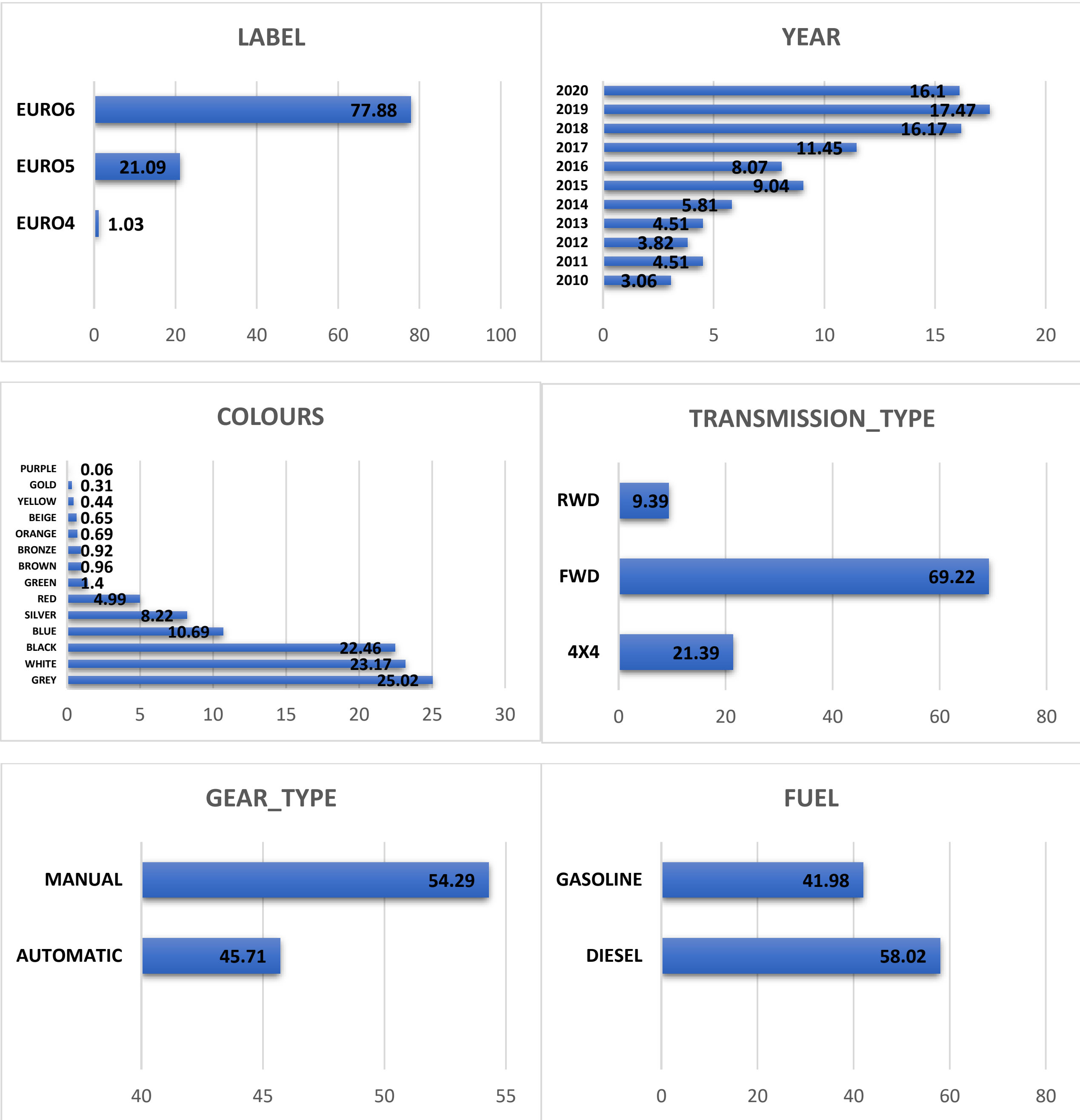
Table 1: the descriptive statistic of the quantitative variables considered in Model M.3.

	PRICE	FUELCOMBO	CO2	KM	HP	CC
Mean	20863.42	5.08	126.00	69928.96	135.32	1,631.83
SD	11891.17	0.9811477	22.74	49343.62	53.87	464.59
Variance	1.41E+08	0.9626509	517.12	2430000000.00	2,902.45	215,840.20
p25	12500	4.30	110.00	30100.00	95.00	1,248.00
p50	17900	5.00	121.00	59900.00	120.00	1,560.00
p75	26890	5.70	139.00	98000.00	160.00	1,984.00
Range	90800	6.20	147.00	368999.00	410.00	2,623.00
Min	2200	2.00	85.00	1.00	60.00	875.00
Max	93000	8.20	232.00	369000.00	470.00	3,498.00
N	4769	4769	4528	4769	4769	4769

Source: author.

On the other hand, in the main models derived from the Milan Dataset, there are also a series of qualitative variables. So, as a reliable illustrative example, Figure 1 displays the percentage frequency of the various categories of six out of seven categorical variables of Model M.3; the last one is MODEL, which reflects the various considered brand and model combinations and has, for example, 196 categories in Model M.3 (in this model the three most frequent models are Volkswagen Golf with 185 statistical units, Audi A4 with 116 and Audi A3 with 114). It is important to underline that in all the models of section 4.2, in which there are these factorial variables, the reference group is always the most numerous one.

Figure 1: the frequency of the various categories of the six categorical variables of Model M.3.



Source: author.

3.6 Descriptive statistics: the Panda dataset

The second cross-sectional dataset, the so-called Panda dataset, similarly was used to develop a hedonic analysis to estimate the price elasticity (or semi-elasticity) of the considered used Fiat Panda in relation to their studied independent environmental variables. Specifically, it was employed a subset derived from the Panda database made of 1950 observations for all the Panda HPMs of section 4.3

Table 2 shows the descriptive statistic of the level form of the considered quantitative variables.

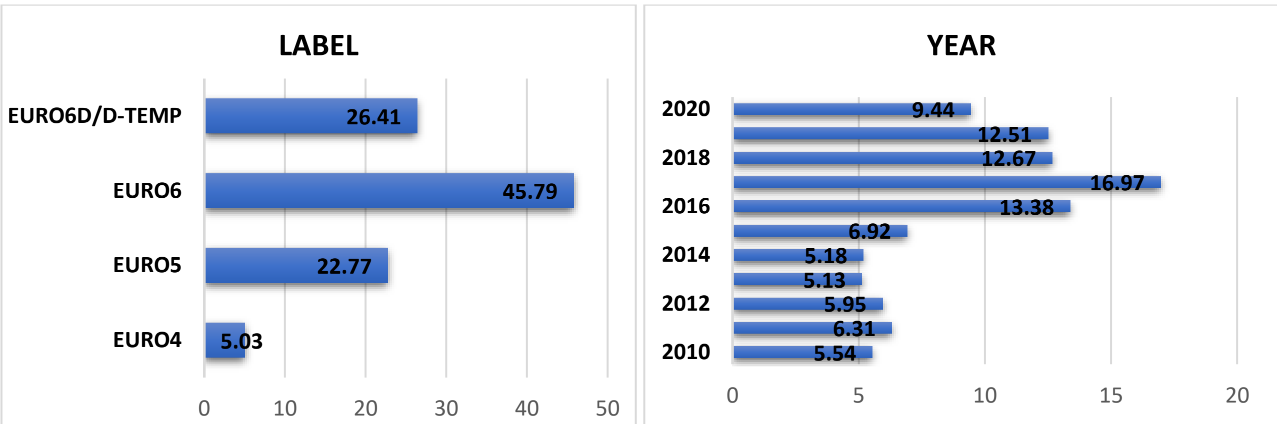
Table 2: descriptive statistic of the considered quantitative variables.

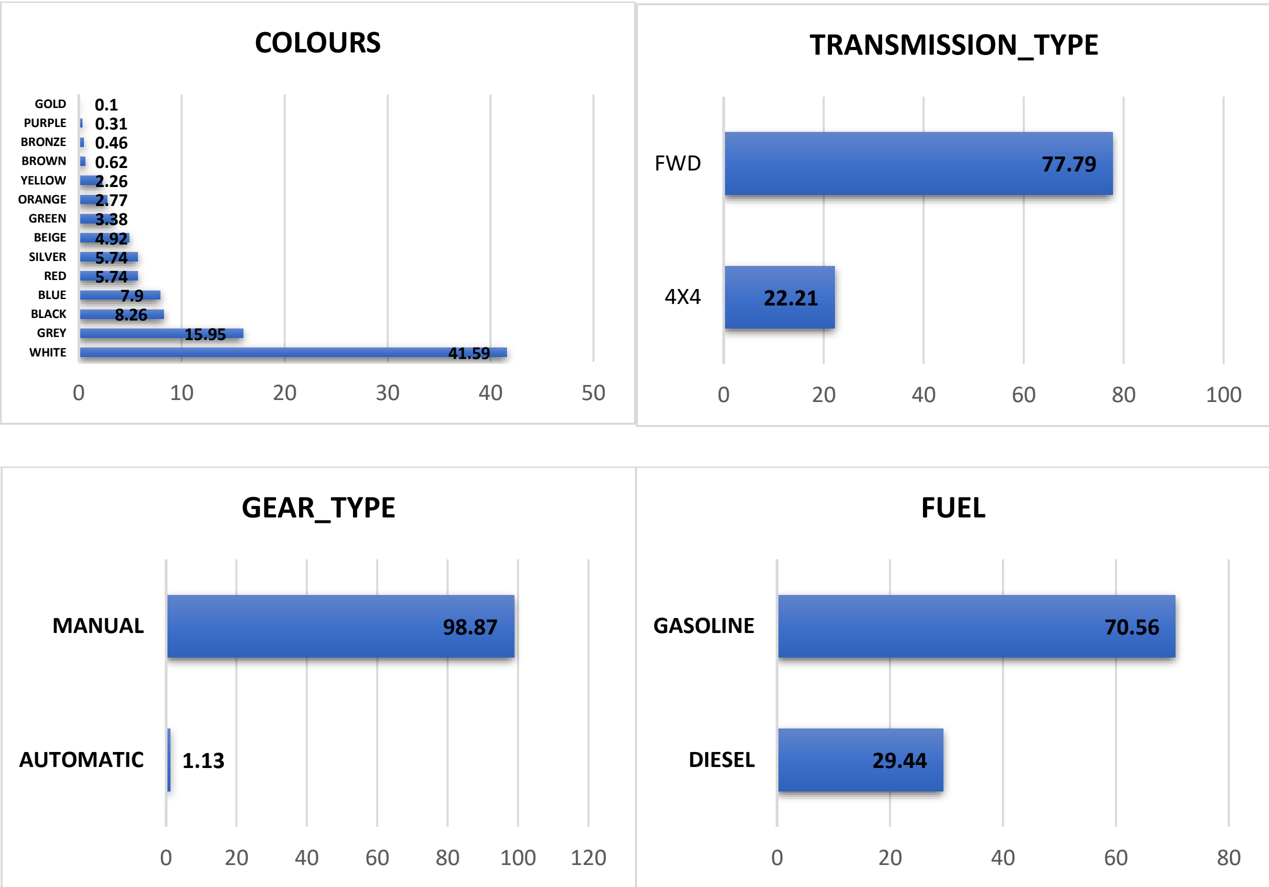
	PRICE	FUELCOMBO	CO2	KM	HP	CC
Mean	9860.01	4.78	114.95	70583.19	75.08	1196.88
SD	3016.68	0.57	10.16	59265.66	9.82	121.93
Variance	9100342.00	0.32	103.25	3510000000.00	96.44	14866.06
p25	7900.00	4.50	111.00	33193.00	69.00	1242.00
p50	9800.00	4.90	116.00	60000.00	69.00	1242.00
p75	11500.00	5.10	119.00	96533.00	80.00	1248.00
Range	17950.00	3.60	70.00	1679774.00	46.00	493.00
Min	1950.00	3.00	85.00	10.00	54.00	875.00
Max	19900.00	6.60	155.00	1679784.00	100.00	1368.00
N	1950	1950	1950	1950	1950	1950

Source: author.

On the other hand, in the main models derived from the Panda dataset, there are also a series of qualitative variables. Figure 2 displays the percentage frequency of the various categories of the six categorical variables of the Panda HPMs It is important to underline that in all the models of section 4.3, in which there are these factorial variables, the reference group is always the most numerous one.

Figure 2: the frequency of the various categories of the six factorial variables of the Panda HPMs.





Source: author.

4. Econometric models and results

4.1 The Milan and the Panda HPMs

In this paper's models, the customers are supposed to choose a set of cars' attributes that maximises their utility. The consumer's budget is the principal limitation of this maximisation process (Mustafa & Kostak, 2021); however, also personal, and in particular environmental values are significant for the determination, at least in a partial way, of the people's consumption choices in relation to transport (Kahn, 2007; Prieto & Caemmerer, 2013).

In the HPMs derived from both the Milan and the Panda Datasets, the multivariate regression models used to estimate the studied coefficients are of this type (here in particular for Model M.1):

$$\boldsymbol{ln}(\boldsymbol{PRICE_i}) = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 ln}(\boldsymbol{FUELCOMBO_i}) + \boldsymbol{\beta_2 ln}(\boldsymbol{CO2_i}) + \boldsymbol{\beta_3 D}(\boldsymbol{EURO4_i}) + \boldsymbol{\beta_4 D}(\boldsymbol{EURO5_i}) + \boldsymbol{\beta_5 ln}(\boldsymbol{HP_i}) + \boldsymbol{\beta_6 ln}(\boldsymbol{CC_i}) + \boldsymbol{\beta_7 ln}(\boldsymbol{KM_i}) + \boldsymbol{\beta_j D}\left(\boldsymbol{X_{ij}}\right) + \boldsymbol{\varepsilon_i}$$

In Equation (1), $PRICE_i$ is the price of the i-th considered cars, β_0 is the standard regression intercept, β_j is the regression coefficient for the j-th product characteristic and x_{ij} is the j-th characteristic of the i-th considered vehicles and ε_i is the error term.

In the considered models of sections 4.2 and 4.3, all the quantitative variables have been subject to a log-transformation since this logarithmic form implies a linear relation in a relative manner (constant elasticity) instead of an absolute one, reflecting better the relations between the explained and the explanatory variables.

The regression coefficients of $\boldsymbol{log}(\boldsymbol{FUELCOMBO_i})$ and of $\boldsymbol{log}(\boldsymbol{CO2_i})$ must be interpreted as partial elasticities, since both the dependent and these two independent variables are logged. So, the two coefficients $\boldsymbol{\beta_1}$ and $\boldsymbol{\beta_2}$ are approximately equal to the percentage change of PRICE when FUELCOMBO and CO2 change by one percent (Brachinger, 2002).

More specifically, in case coefficients in the studied quantitative variable (like FUELCOMBO) were found, it would be possible to interpret them as how a 1% decrease is expected to increase, on average and ceteris paribus, the automobiles' cost by a percentage change, by applying the formula of Equation (2) – in which β is the given independent variables' coefficient (Wooldridge, 2015):

$$\%\Delta\text{PRICE} = 100 \times (0.99^{\beta} - 1) \tag{2}$$

Whereas the regression coefficient of the studied dummy variables accounting for the European emission categories must be interpreted as semi-elasticity. So, the three coefficients $\boldsymbol{\beta_4}$, $\boldsymbol{\beta_5}$, $\boldsymbol{\beta_6}$ are equal to the percentage change in the dependent variable (PRICE) given the fact that the dummy is equal to 1. This percentage change can be calculated, for example for the coefficient $\boldsymbol{\beta_4}$, through the Equation (3) in this manner (Halvorsen & Palmquist, 1980; Wooldridge, 2015):

$$\%\Delta PRICE = 100 \cdot [exp(\beta_4) - 1] \tag{3}$$

However, by applying Equation (4)'s formula, it is possible to estimate the percentage change in the dependent variable (PRICE) given the fact that the dummies for the European Emission classes switches from 1 to 0 (Wooldridge, 2015), calculating, in this way, the price premium of EURO 6 compared to the other considered emission categories:

$$\%\Delta PRICE = 100 \cdot [exp(-\beta_j) - 1] \tag{4}$$

4.2 The estimated results of the Milan hedonic models

Table 3 shows the results estimated thanks to the HPMs derived from the Milan Dataset.

In Model M.1, the coefficient of LN_FUELCMBO is negative and significant at the 0.01 level. More precisely, the estimated elasticity of PRICE with respect to FUELCOMBO is equal to -0.168, indicating that a 1% decrease in FUELCOMBO is predicted to rise, on average, the used cars' cost by 0.169%, ceteris paribus. In contrast, in this model, the other studied quantitative variable, namely LN_CO2 is positive but not statistically significant and its coefficient shows that a 1% increase in CO2 is expected to rise, on average, the vehicles' price by 0.062%. Finally, the coefficient of the two dummies accounting for the European emission categories are both negative and not significant from a statistical point of view, and indicate that, ceteris paribus, the estimated price premium of EURO 6 cars is equal to 2.22% in comparison to EURO 5 cars, and to 5.25% in comparison to EURO 4 vehicles.

Finally, in this model, the studied explanatory variables' variance inflation factor (VIF), which is the measure used to assess the presence of the potential issue of multicollinearity, is equal to 13.95 for LN_FUELCOMBO, 13.90 for LN_CO2, 1.74 for the EURO 4 dummy and 4.59 for the EURO 5 one. In particular, the VIF method is used to evaluate the presence of multicollinearity, by observing the extent to which a considered predictor variable can be explained by all the other explanatory variables of the model, fostering, as a result, the variance of the estimated coefficients. A high value for the VIF, namely a VIF higher than 10, designates that multicollinearity has problematically decreased the precision of the estimated coefficients (Studenmund, 2014). So, because the VIF of LN_FUELCOMBO and of LN_CO2 is higher than 10, it is possible to sustain that Model M.1 is affected by the issue of multicollinearity

To address the problem of multicollinearity of these studied quantitative independent variables, one at a time are excluded, as done, for the same reason by Wells et al. (2013).

So, in model M.3, LN_CO2 is dropped, and, as a result, the VIF of LN_FUELCOMBO is now equal to 5.69, a more tolerable figure than the one of Model M.1.
In Model M.3, in addition, the coefficient of LN_FUELCMBO is negative, significant at the 0.01 level and equal to -0.128 indicating that a 1% decrease in FUELCOMBO is predicted to rise, on average, the second-hand cars cost by 0.129%, ceteris paribus.

In an analogous way, in Model M.4, LN_FUELCOMBO is dropped, and thanks to this, the VIF of LN_CO2 is now equal to 5.69, again a more acceptable figure compared to the one of Model M.1.
In Model M.3, the coefficient of LN_CO2 is negative, significant at the 0.05 level and equal to -0.0799, indicating that a 1% increase in CO2 is predicted to diminish, ceteris paribus and on average, the cars cost by 0.079%.

Finally, thanks to Model M.2, it is possible to understand the impact of the categorical variable YEAR on the coefficient of the studied factorial variable LABEL. More precisely, Model M.2 is identical to Model M.1 except for the fact that in the former the categorical variable YEAR is dropped, significantly fostering the size of the coefficients of the two dummies accounting for the European emission categories, and indicating, as a consequence, that the two categorical variables of LABEL and YEAR could be related. So, a chi-square test of independence between these two categorical variables is performed, and the p-value of the test turns out to be equal to 0.000. Because of this figure, it was not possible to reject the null hypothesis for which the two categorical variables are independent. This result indicates that there is a statistically significant association between the considered cars' year and their European emission categories. Finally, in Model M.2, the two coefficients of EURO 4 and EURO 5 remain negative, become significant at the 0.01 level, bigger in absolute value and suggest that, ceteris paribus, the estimated price premium of EURO 6 vehicles is equal to 46.96% compared to EURO 5 cars and to 84.04% compared to EURO 4 ones.

Table 3: the estimated results of the models based on the observations of the Milan dataset.

VARIABLES	Model M.1	Model M.2	Model M.3	Model M.4
LN_FUELCOMBO[1]	-0.168***	-0.179***	-0.128***	
	(0.0478)	(0.0634)	(0.0301)	
LN_CO2[2]	0.0622	-0.0660		-0.0799**
	(0.0523)	(0.0688)		(0.0345)
LN_CC	0.0261	-0.0342	0.0306	0.0217
	(0.0244)	(0.0306)	(0.0233)	(0.0244)
LN_HP	0.454***	0.497***	0.452***	0.450***
	(0.0231)	(0.0267)	(0.0226)	(0.0231)
LN_KM	-0.0965***	-0.188***	-0.0988***	-0.0967***
	(0.0102)	(0.0128)	(0.0101)	(0.0102)
EURO 4[3]	-0.0512	-0.610***	-0.0382	-0.0537
	(0.0407)	(0.0384)	(0.0393)	(0.0407)
EURO 5[4]	-0.0220	-0.385***	-0.0234	-0.0233
	(0.0144)	(0.0126)	(0.0144)	(0.0144)
GASOLINE	0.0211	0.0101	0.0186	-0.00565
	(0.0139)	(0.0182)	(0.0134)	(0.0113)
AUTOMATIC	0.0678***	0.0895***	0.0663***	0.0687***
	(0.00664)	(0.00862)	(0.00636)	(0.00665)
4X4	0.0526***	0.0313**	0.0559***	0.0491***
	(0.0104)	(0.0131)	(0.00998)	(0.0103)
RWD	-0.0379**	-0.0621***	-0.0343**	-0.0433***
	(0.0150)	(0.0210)	(0.0146)	(0.0150)
DUMMIES FOR YEARS	✓	✗	✓	✓
DUMMIES FOR COLOURS	✓	✓	✓	✓
DUMMIES FOR MODELS	✓	✓	✓	✓
CONSTANT	8.566***	10.32***	8.799***	9.048***

[1] **LN_FUELCOMBO:** the studied independent variable accounting for cars' fuel efficiency (measured in litres per 100 kilometres).
[2] **LN_CO2:** the studied independent variable accounting for vehicles' carbon dioxide emissions (measured in grams per kilometre).
[3] **EURO 4:** the studied independent dummy variable reflecting vehicles' belonging to the EURO 4 class of the European emission categories (the base group are EURO 6 cars).
[4] **EURO 5:** the studied independent dummy variable reflecting vehicles' belonging to the EURO 5 class of the European emission categories (the base group are EURO 6 cars).

	(0.252)	(0.312)	(0.196)	(0.213)
OBSERVATIONS	4,528	4,528	4,769	4,529
R-SQUARED	0.935	0.894	0.935	0.935

Robust standard errors in parentheses. P-values: *** p<0.01, ** p<0.05, * p<0.1.

Source: author.

4.3 The estimated results of the Panda hedonic models

Table 4 presents the estimated results of the HPMs derived from the Panda dataset.

In Model P.1, the coefficient of LN_FUELCMBO is negative but not significant from a statistical point of view. In particular, in this model the estimated elasticity of PRICE with respect to FUELCOMBO is equal to -0.0780, indicating that, ceteris paribus, a 1% decrease in FUELCOMBO is predicted to rise, on average, the considered Fiat Panda vehicles cost by 0.078%. Conversely, the other studied quantitative variable, namely LN_CO2 is positive and statistically significant at the 0.01 level and its coefficient shows that a 1% increase in CO2 is expected to rise, on average, the vehicles' price by 0.337%, ceteris paribus. Finally, the estimated coefficient of two of the three dummies accounting for the European emission categories, namely EURO 4 and EURO 5, have a counterintuitive positive sign. More specifically, the coefficient of EURO 4 is equal to 0.104 and is not statistically significant, whereas the one of EURO 5 is equal to 0.0694 and significant at the 0.01 level. This latter suggests that, ceteris paribus, in comparison to EURO 5 models, EURO 6 Panda are priced 6.705% less. On the other hand, this time as expected, the estimated coefficient of the last considered dummy of the categorical variable LABEL, namely the EURO 6D/6D-TEMP one, has a positive sign, is significant at the 0.10 level, and indicates that, all else being equal, the cost of a used EURO 6 Panda is 3.043% lower than the one of a EURO 6D/6D-TEMP.

Finally, in the Model P.1, the variance inflation factors (VIF) of the studied explanatory variables are equal to 6.36 for LN_FUELCOMBO, 5.07 for LN_CO2, 7.10 for EURO 4, 6.63 for EURO 5 and 6.56 for EURO 6D/6D-TEMP. These VIF values, despite not being especially small, are not problematic.

As above mentioned, in Model P.1 the estimated negative coefficient of LN_FUELCOMBO is not statistically significant. To address this issue, in model P.2 the quantitative control variables of LN_CC, of LN_HP, and of LN_KM are considered in their level-form, and thanks to this, the coefficient of LN_FUELCOMBO become statistically significant at the 0.05 level.

Returning to the problem of the counterintuitive coefficients of the two dummies (ERUO 4 and EURO 5) of the categorical variable LABEL in Model P.1, thanks to Model P.3, it is possible to understand the impact of the factorial variable YEAR on the coefficient of the studied categorical variable for the European emission classes in the consimilar Model P.1. More precisely, model P.3 is identical to model P.1 except for the fact that in the former the categorical variable YEAR is excluded, fostering considerably, as a result, the size of the coefficients of the two given dummies, and, indicating, as a result, that the two categorical variables of LABEL and YEAR could be related. So, a chi-square test of independence between these two categorical is performed, and the p-value of the test turns out to be equal to 0.000. Because of this finding, it was not possible to reject the null hypothesis for which the two factorial variables are independent. This result indicates that there is a statistically significant association between the considered Fiat Panda cars' registration year and their European emission categories. So, in model P.3, in which the factorial variable YEAR is excluded, the two coefficients of EURO 4 and EURO 5 appear as negative and significant at the 0.01 level, suggesting that, ceteris paribus, EURO 6 Fiat Panda are sold for 31.92% more in comparison to EURO 5 ones, and for 64.87% more in comparison to EURO 4 ones. It must be underlined, in addition, that the coefficient of the dummy EURO 6D/6D-TEMP is greater in its size (0.138) compared to the one of model P.1 (0.0309), indicating that, ceteris paribus, EURO 6 Fiat Panda costs 12.89% less compared to the EURO 6D/6D-TEMP ones.

Moreover, Model P.4 and P.6 were created to understand the effect of the exclusion of one of the two studied quantitative independent variable, namely LN_FUELCOMBO and LN_CO2, which are relatively highly correlated due to their pairwise Pearson correlation coefficient of 0.776. So, in model P.4, in which LN_CO2 is excluded, the coefficient of LN_FUELCOMBO has a positive sign (instead of the negative one of Model P.1), is not statistically significant and is equal to 0.0832, showing that a 1% increase in FUELCOMBO is predicted to rise, on average, the considered Fiat Panda cost by roughly 0.083%, ceteris paribus. On the other hand, in Model P.6, in which LN_FUELCOMBO is excluded, the coefficient of LN_CO2 has a positive sign (like in all the other Panda HPMs), is statistically significant at the 0.01 level and is equal to 0.281, showing that a 1% increase in CO2 is predicted to rise, on average, the considered Fiat Panda cars cost by roughly 0.280%, ceteris paribus.

Finally, in Model P.5, a model identical to Model P.4, with the sole exception of the exclusion of the factorial variable YEAR, the coefficient of LN_FUELCOMBO returns negative, but not statistically significant and not particularly big in its size (-0.0146).

.

Table 4: the results of the models based on the observations of the Panda dataset.

VARIABLES	Model P.1	Model P.2	Model P.3	Model P.4	Model P.5	Model P.6
LN_FUELCOMBO[5]	-0.0780	-0.129**	-0.207***	0.0832	-0.0146	
	(0.0648)	(0.0638)	(0.0769)	(0.0590)	(0.0699)	
LN_CO2[6]	0.338***	0.424***	0.399***			0.281***
	(0.0876)	(0.0821)	(0.0977)			(0.0768)
LN_CC	0.345***		0.136*	0.395***	0.193***	0.342***
	(0.0645)		(0.0708)	(0.0621)	(0.0691)	(0.0642)
CC		0.000299***				
		(6.98e-05)				
LN_HP	0.731***		0.460***	0.664***	0.378***	0.735***
	(0.0721)		(0.0823)	(0.0704)	(0.0819)	(0.0721)
HP		0.00982***				
		(0.00104)				
LN_KM	-0.0827***		-0.110***	-0.0842***	-0.111***	-0.0828***
	(0.00973)		(0.0114)	(0.00959)	(0.0113)	(0.00971)
KM		-1.07e-06*				
		(5.56e-07)				
LN_GEAR						
LN_N_CYL						
EURO 4[7]	0.104	0.125**	-0.500***	0.104	-0.506***	0.101
	(0.0641)	(0.0601)	(0.0307)	(0.0635)	(0.0306)	(0.0639)
EURO 5[8]	0.0694***	0.0845***	-0.277***	0.0687***	-0.280***	0.0702***
	(0.0227)	(0.0227)	(0.0149)	(0.0229)	(0.0151)	(0.0227)

[5] **LN_FUELCOMBO:** the studied independent variable accounting for Fiat Panda models' fuel efficiency (measured in litres per 100 kilometres).

[6] **LN_CO2:** the studied independent variable accounting for Fiat Panda models' carbon dioxide emissions (measured in grams per kilometre).

[7] **EURO 4:** the studied independent dummy variable reflecting Fiat Panda models' belonging to the EURO 4 class of the European emission categories (the base group are EURO 6 cars).

[8] **EURO 5:** the studied independent dummy variable reflecting Fiat Panda models' belonging to the EURO 5 class of the European emission categories (the base group are EURO 6 cars).

EURO 6D/6D-TEMP[9]	0.0309*	0.0373**	0.138***	0.0375**	0.135***	0.0318*
	(0.0169)	(0.0169)	(0.0111)	(0.0176)	(0.0110)	(0.0170)
DIESEL	-0.0697***	-0.0793**	0.0498*	-0.0630**	0.0591**	-0.0588**
	(0.0255)	(0.0374)	(0.0285)	(0.0258)	(0.0289)	(0.0231)
AUTOMATIC	0.133***	0.143***	0.130***	0.135***	0.133***	0.135***
	(0.0277)	(0.0297)	(0.0316)	(0.0271)	(0.0313)	(0.0276)
4X4	0.306***	0.298***	0.301***	0.340***	0.341***	0.304***
	(0.0187)	(0.0178)	(0.0220)	(0.0147)	(0.0181)	(0.0187)
DUMMIES FOR YEARS	✓	✓	✗	✓	✗	✓
DUMMIES FOR COLOURS	✓	✓	✓	✓	✓	✓
CONSTANT	2.993***	6.326***	5.784***	4.284***	7.321***	3.137***
	(0.750)	(0.397)	(0.834)	(0.685)	(0.773)	(0.730)
OBSERVATIONS	1,950	1,950	1,950	1,950	1,950	1,950
R-SQUARED	0.829	0.833	0.756	0.828	0.754	0.829
Robust standard errors in parentheses. P-values: *** p<0.01, ** p<0.05, * p<0.1.						

Source: author.

[9] **EURO 6D/6D-TEMP:** the studied independent dummy variable reflecting Fiat Panda models' belonging to the EURO 6D/6D-TEMP class of the European emission categories (the base group are EURO 6 cars).

4.4 Comparison of the findings between models

Comparing the results of the HPMs derived from the Milan dataset and the ones derived from the Panda data frame, it is clear that the estimated coefficients of the former are more robust and reliable. In fact, by looking at the first studied quantitative independent variable, namely the considered cars' combined fuel efficiency (LN_FUELCOMBO), its coefficient sign remains negative in all the Milan HPMs of section 4.2, whereas in one of the Panda models of section 4.3, it appears as positive, namely in Model P.4, despite not being statistically significant. More specifically, in Model P.4 the coefficient is positive due to the exclusion of the other quantitative environmental independent variable, i.e., LN_CO2.

On the other hand, with respect to the second studied quantitative independent variable, namely the considered cars' carbon dioxide emission (LN_CO2), its coefficient sign is positive in all the considered Panda models, indicating that a 1% increase in CO2, is expected to increase, on average, the cost of the considered Panda' vehicles by a positive percentage rise (from 0.281% of Model P.6 to 0.424% of Model P.2). In addition, it is relevant to underline that, if in Model P.6 the categorical variable LABEL and YEAR are excluded, the coefficient of LN_CO2 remains positive, although a little smaller (0.177 vs 0.281 of Model P.6). Furthermore, it is also important to highlight that when LN_FUELCOMBO and LN_CO2 are included alongside in the Panda HPMs (as in Model P.2 and P.3), both their coefficients' size increase in absolute terms. This finding is in contrast with the one of Kuru (2017), which discovered that the estimated coefficient for fuel efficiency decreased significantly in absolute terms after the integration in the model of variables reflecting the given cars' pollution level. Differently, in the Milan models, when LN_FUELCOMBO and LN_CO2 are included alongside in the HPMs (as in Model M.2), only the size of the coefficient of the former rises in absolute terms.

Returning to the analysis of the sole coefficient of LN_CO2, in the principal Milan models, in contrast to the findings of the Panda ones, this studied variable's coefficients are particularly small and with a shifting sign. On the other hand, the estimated positive MWTP for CO2 found in all the Panda HPMs could be explained by a peculiar price premium of this specific model and/or its segment, namely the one of mini cars (A-segment).

Eventually, in relation to the third studied independent variable, namely the dummy variables for the European emission categories of the considered automobiles, in both the Milan and the Panda models, the related coefficients' size and sign - this latter only for the Panda models - are reduced and changed, because of the inclusion in the HPMs of the factorial variable YEAR, which accounts for the year of the given vehicles' first registration and is associated with LABEL.

Finally, ceteris paribus, the estimated MWTP, derived from the Milan models, for the cars with the higher European emission classes could be explained, at least partially, by the guaranteed access to city centres provided by them. To test this more thoroughly, in both Model M.1 (in which YEAR is included) and in Model M.2 (in which YEAR is not considered), an interaction term between the two categorical variables LABEL and FUEL was added, and it resulted that, ceteris paribus, the price premium of a gasoline EURO 4 cars, compared to a diesel EURO 4 one, is equal to 11.59% in the former model and to 7.75% in the latter one. However, only in the versions of Model M.1 with this interaction term, this latter is statistically significant (at the 0.10 level). This estimated result is particularly interesting because it implies that a vehicle, equal in all other features, but not subject, due to its fuel type, to circulation restrictions, is characterized by a positive price premium.

5. Conclusion

The objective of this paper was to estimate, through two original datasets and the hedonic pricing method, the MWTP for three environmental features of cars: namely their fuel efficiency (measured in litres per 100 kilometres), their CO_2 emissions (measured in grams per kilometre), and their belonging to one of the European emission classes.

In particular, these two data frames (i.e., the Panda and the Milan ones) were considered to have more robust findings from different perspectives and to address, at least partially, the issue of market segmentation.

It was expected that the HPMs of this work would have been able to consistently find a positive MWTP only for an improved level of FUELCOMBO and not for a diminished level of CO2, since cars' fuel economy enters directly into the consumers' utility optimization function through customers' budget constraint, when they buy a used car; conversely, a willingness to pay for automobiles with a reduced level of CO_2 emissions is typical of the restricted group of consumers with environmentalist values, who are ready to partially internalize the externality related to the pollutants emitted by their vehicles (Alberini et al., 2014).
Finally, this study has estimated a relevant price premium for vehicles that comply with the higher European emission classes.

The policy implications that can be derived from this work is a support for further investments in policies that will encourage the purchases of used cars with a high degree of the three considered environmental attributes, and, at the same time, the dismantling of the oldest and most polluting vehicles.

Regulators, indeed, should concentrate their efforts more on owners of outdated, fuel-inefficient vehicles, by designing measures to stimulate the substitution of such cars with fuel-efficient ones (Nakamoto & Kagawa, 2022).

An example of these policies is, for instance, rebate schemes for buying used cars with a EURO 6 or higher European emission category. In 2021, it has been established a scrappage system of this type in Italy, which has given a subsidy for the purchases of used vehicles with an emission class not lower than EURO 6, a price resulting from average market quotations of no more than 25,000 euros and with CO_2 emissions between 0-160 grams per kilometre. Moreover, the decommissioned car must have an emission class lower than Euro 5 (MISE, 2022).

Nevertheless, in 2021, the first year in which the above-mentioned Italian scrappage scheme was in force with an allocated budget of 40 million of euros, a significant portion of the used automobiles' sales between privates still involved 1,300,598 cars with a European emission category prior to EURO 5 (43% of the total, with a growth of 6.91% of their trades in absolute value on a yearly basis) (ACI, 2022, 2021).

To design better scrappage policies, the amount of the conferred subsidy could be increased depending on the fuel efficiency and year of production of the dismantled vehicles, after having assessed an optimal target age for the used vehicles' disposal. Drivers should be able to choose between numerous alternatives of new or used fuel-efficient automobile, reducing, as a result, the opportunity costs at the moment of car substitution (Nakamoto & Kagawa, 2022).

The common problematics of the methodology - the hedonic pricing method - used in this work are inaccurately measured variables, model misspecification, the issue of multicollinearity and the one about the potential relationships between the omitted and included variables. Because of them, it is extremely hard to precisely estimate consumers' MWTP for car characteristics (Greene, 2018).

In addition to these common methodological issues, the current study presents three main specific limitations.

Firstly, the used functional forms, namely the log-log and semi-log ones may not be the most appropriate. It would be useful to check the estimated coefficients of this work, by employing a more complex functional form, like a Box-Cox one, in order to make a comparison with the findings of the simpler forms employed in this study (Chau & Chin, 2003; Box & Cox, 1964). The author of this work decided to use the above-mentioned easier functional forms because of their simplicity of interpretation.

Secondly, the usage of independently pooled cross-sectional data could have been useful to estimate more precise and less biased results for the studied variables of this paper.

Thirdly, the issue of market segmentation, which is another debated problematic of the hedonic pricing method, linked to the necessity of using a correct sample selection for assessing appropriately the given hedonic price function of the population of interest. In particular, if market segmentation is present in the studied market, the hedonic pricing function that is calculated for its entirety will produce inaccurate estimated evaluations of the implicit prices of its various market segments (Freeman, 1981). In this paper, as mentioned above, in order to partially cope with the problem of market segmentation, two different datasets were considered. It is relevant to underline, however, that the findings of this work and, specifically, the estimated coefficients of the Milan HPMs cannot be inferred to the entire Italian secondary car market. Indeed, the composition of the Milan sub-samples used for the models of section 4.2 does not precisely reflect the Italian used car market. So, future studies could create a stratified random sample almost perfectly reflecting the studied population by employing ACI's data (ACI, 2022), to analyse more accurately the Italian second-hand car market. Moreover, to complete the picture of this work, and in particular, of the analysis provided by the Panda HPMs, it would be worthwhile to estimate distinct hedonic price functions of other cars' segments, like the B-segment of small cars (represented, for instance, by the Volkswagen Polo) (EEC, 1999). In further studies, similarly, the outcome of the Panda HPMs about the price premium of CO_2 could be more thoroughly confirmed, by considering, as statistical units, other vehicles of the Panda's class (the A-segment), like the Toyota Aygo and the Fiat 500.

References

ACI. (2020). Autoritratto 2020. Available at: https://www.aci.it/laci/studi-e-ricerche/dati-e-statistiche/autoritratto/autoritratto-2020.html

ACI. (2021). Autoritratto 2021. Available at: https://www.aci.it/laci/studi-e-ricerche/dati-e-statistiche/autoritratto/autoritratto-2021.html

Alberini, A., Bareit, M., & Filippini, M. (2014). Does the Swiss car market reward fuel efficient cars? Evidence from Hedonic pricing regressions, matching and a regression discontinuity design. *Evidence from Hedonic Pricing Regressions, Matching and a Regression Discontinuity Design (January 16, 2014). CER-ETH Economics Working Paper*, (14/190).

Alberini, A., Bareit, M., & Filippini, M. (2016). What is the effect of fuel efficiency information on car prices? Evidence from Switzerland. *The Energy Journal*, *37*(3).

Allcott, H., & Wozny, N. (2013). Gasoline prices, fuel economy, and the energy paradox. *Review of Economics and Statistics*, *96*(5), 779-795.

Anderson, S. T., Parry, I. W., Sallee, J. M., & Fischer, C. (2020). Automobile fuel economy standards: Impacts, efficiency, and alternatives. *Review of Environmental Economics and Policy*.

Arguea, N. M., & Hsiao, C. (1993). Econometric issues of estimating hedonic price functions: With an application to the US market for automobiles. *Journal of Econometrics*, *56*(1-2), 243-267.

Atkinson, S. E., & Halvorsen, R. (1984). A new hedonic technique for estimating attribute demand: an application to the demand for automobile fuel efficiency. *The Review of Economics and Statistics*, 417-426.

AutoScout24. (2020a). Company profile. Available at: https://www.autoscout24.com/company/about-autoscout24/company-profile/portrait/

AutoScout24. (2020b). AutoScout24 – Tutto sulle auto. Available at: https://www.autoscout24.it/azienda/chi-siamo/autoscout24-italia-profilo-aziendale/autoscout24-tutto-sulle-auto/

Bar-Ilan, J. (2001). Data collection methods on the Web for infometric purposes—A review and analysis. *Scientometrics*, *50*(1), 7-32.

Bento, A. M., Goulder, L. H., Jacobsen, M. R., & Von Haefen, R. H. (2009). Distributional and efficiency impacts of increased US gasoline taxes. *American Economic Review*, *99*(3), 667-99.

Bin, O., & Martins-Filho, C. (2008). Vehicle price and hydrocarbon emissions: evidence from the used-vehicle markets. *Applied Economics Letters*, *15*(12), 939-943.

Box, G. E., & Cox, D. R. (1964). An analysis of transformations. *Journal of the Royal Statistical Society: Series B (Methodological)*, *26*(2), 211-243.

Brachinger, H. W. (2002). *Statistical theory of hedonic price indices*. Université de Fribourg.

Chau, K. W., & Chin, T. L. (2003). A critical review of literature on the hedonic price model. *International Journal for Housing Science and Its Applications*, *27*(2), 145-165.

Chugh, R., Cropper, M., & Narain, U. (2011). The cost of fuel economy in the Indian passenger vehicle market. *Energy Policy*, *39*(11), 7174-7183.

Colantone, I., Di Lonardo, L., Margalit, Y., & Percoco, M. (2022). The Political Consequences of Green Policies: Evidence from Italy.

Council Directive. (1970). Council Directive 70/220/EEC of 20 March 1970 on the approximation of the laws of the Member States relating to measures to be taken against air pollution by gases from positive-ignition engines of motor vehicles Official Journal L 76, 6 April 1970, pp. 1-22. Official Journal L, 76, 1-22.

Doležalová, R. (2020). What is My Car Worth? Hedonic Price Analysis of the German Used Car Market.

EEC. (1999). Commission of the European communities, Case No COMP/M.1406 — Hyundai / KIA, Regulation (EEC), No. 4064/89, 1999. Available at: https://ec.europa.eu/competition/mergers/cases/decisions/m1406_en.pdf.

Espey, M., & Nair, S. (2005). Automobile fuel economy: What is it worth?. *Contemporary Economic Policy*, *23*(3), 317-323.

Freeman III, A. M. (1981). Hedonic prices, property values and measuring environmental benefits: a survey of the issues. In Measurement in public choice (pp. 13-32). Palgrave Macmillan, London.

Galarraga, I., Ramos, A., Lucas, J., & Labandeira, X. (2014). The price of energy efficiency in the Spanish car market. *Transport Policy*, *36*, 272-282.

GFEI. (2020). Vehicle Efficiency and Electrification: A Global Status Report: Global Fuel Economy Initiative (GFEI).

Goodman, A. C. (1983). Willingness to pay for car efficiency: A hedonic price approach. *Journal of Transport Economics and Policy*, 247-266.

Gota, S., Huizenga, C., Peet, K., & Kaar, g. (2015). Emission reduction potential in the transport sector by 2030. *Slocat. Bejing: Slocat.*

Greene, D., Hossain, A., Hofmann, J., Helfand, G., & Beach, R. (2018). Consumer willingness to pay for vehicle attributes: What do we Know?. *Transportation Research Part A: Policy and Practice*, *118*, 258-279.

Griliches, Z. (1961). 3. Hedonic price indexes for automobiles: an econometric analysis of quality change. In *Price indexes and quality change* (pp. 55-87). Harvard University Press.

Hadinejad, M., & Shabgard, B. (2011). Hedonic Price For Car in Iran. *Sosyal Bilimler Dergisi*, (2), 118-127.

Halim, R. A., Kirstein, L., Merk, O., & Martinez, L. M. (2018). Decarbonization pathways for international maritime transport: A model-based policy impact assessment. *Sustainability*, *10*(7), 2243.

Halvorsen, R., & Palmquist, R. (1980). The interpretation of dummy variables in semilogarithmic equations. *American economic review*, *70*(3), 474-475.

Haq, G., & Weiss, M. (2016). CO2 labelling of passenger cars in Europe: Status, challenges, and future prospects. *Energy Policy*, *95*, 324-335.

ISPRA. (2019). Le emissioni dal trasporto stradale in Italia. Available at: https://www.isprambiente.gov.it/files2021/eventi/evento16apr2021_emissioni_strada.pdf.

Kahn, J. A. (1986). Gasoline prices and the used automobile market: a rational expectations asset price approach. *The Quarterly Journal of Economics*, *101*(2), 323-339.

Kahn, M. E. (2007). Do Greens Drive Hummers or Hybrids? Environmental Ideology as a Determinant of Consumer Choice. *Journal of Environmental Economicsand Management, 54,* 129 – 145.

Kihm, A., & Vance, C. (2016). The determinants of equity transmission between the new and used car markets: a hedonic analysis. *Journal of the Operational Research Society*, *67*(10), 1250-1258.

Knittel, C. R. (2011). Automobiles on steroids: Product attribute trade-offs and technological progress in the automobile sector. *American Economic Review*, *101*(7), 3368-99.

Kuru, A. (2017). *Consumer Valuation of Improvements in Fuel Economy and Reductions in Emissions of Vehicles in Turkey* (Doctoral dissertation, Clemson University).

Lancaster, K. J. (1966). A new approach to consumer theory. *Journal of political economy*, *74*(2), 132-157.

Liu, Y., & Helfand, G. E. (2012). A hedonic test of the effects of the Alternative Motor Fuels Act. *Transportation Research Part A: Policy and Practice*, *46*(10), 1707-1715.

Lutsey, N., & Sperling, D. (2012). Regulatory adaptation: Accommodating electric vehicles in a petroleum world [J]. *Energy Policy*, *45*, 308-316.

Matas, A., & Raymond, J. L. (2009). Hedonic prices for cars: an application to the Spanish car market, 1981–2005. *Applied Economics*, *41*(22), 2887-2904.

MISE. (2022). Ecobonus. Available at: https://ecobonus.mise.gov.it/contributi

Mooney, S. J., Westreich, D. J., & El-Sayed, A. M. (2015). Epidemiology in the era of big data. *Epidemiology (Cambridge, Mass.)*, *26*(3), 390.

Murray, J., & Sarantis, N. (1999). Price-quality relations and hedonic price indexes for cars in the United Kingdom. *International Journal of the Economics of Business*, *6*(1), 5-27.

Mustafa, K. O. Ç., & Kostak, N. (2021). What is happening to used car prices in Turkey? Evidence from Hedonic Price Model (HPM). *Selçuk Üniversitesi Sosyal Bilimler Enstitüsü Dergisi*, (46), 225-240.

Nakamoto, Y. (2017). CO2 reduction potentials through the market expansion and lifetime extension of used cars. *Journal of Economic Structures*, *6*(1), 1-14.

Nakamoto, Y., & Kagawa, S. (2022). A generalized framework for analyzing car lifetime effects on stock, flow, and carbon footprint. Journal of Industrial Ecology, 26(2), 433-447.

Pearce, D., Atkinson, G., & Mourato, S. (2006). *Cost-benefit analysis and the environment: recent developments*. Organisation for Economic Co-operation and development.

Prieto, M., & Caemmerer, B. (2013). An exploration of factors influencing car purchasing decisions. *International Journal of Retail & Distribution Management*.

Regione Lombardia (2022). FAQ Domande frequenti Limitazioni per la qualità dell'aria. Available at: https://www.regione.lombardia.it/wps/wcm/connect/1978f7ad-7668-462e-8c1c-7c2567f5b136/FAQ_Limitazioni_qualit%C3%A0+aria+DEF.pdf?MOD=AJPERES&CACHEID=ROOTWORKSPACE-1978f7ad-7668-462e-8c1c-7c2567f5b136-nll3dLO#:~:text=A%20partire%20dal%201%C2%B0,Giuliano%20Milanese.

Sammer, K., & Wüstenhagen, R. (2006). The influence of eco-labelling on consumer behaviour–Results of a discrete choice analysis for washing machines. *Business Strategy and the Environment*, *15*(3), 185-199.

Studenmund, A. H. (2014). *Using econometrics a practical guide*. Pearson.

Taptich, M. N., Horvath, A., & Chester, M. V. (2016). Worldwide greenhouse gas reduction potentials in transportation by 2050. *Journal of Industrial Ecology*, *20*(2), 329-340.

Teter, J. (2020). Tracking transport 2020.

Tietenberg, T., & Lewis, L. (2019). *Natural Resource Economics: The Essentials*. Routledge.

UNRAE. (2021). Analisi Del Mercato Autoveicoli in Italia. Available at: https://unrae.it/files/Book%20UNRAE%202021_624d7464bc0a7.pdf

Van Amstel, M., Driessen, P., & Glasbergen, P. (2008). Eco-labeling and information asymmetry: a comparison of five eco-labels in the Netherlands. *Journal of Cleaner Production*, *16*(3), 263-276.

Wells, P., Varma, A., Newman, D., Kay, D., Gibson, G., Beevor, J., & Skinner, I. (2013). Governmental regulation impact on producers and consumers: A longitudinal analysis of the European automotive market. *Transportation Research Part A: Policy and Practice*, *47*, 28-41.

West, S. E., & Williams III, R. C. (2005). The cost of reducing gasoline consumption. *American Economic Review*, *95*(2), 294-299.

Witt, R. (1997). The demand for car fuel efficiency: some evidence for the UK. *Applied Economics*, *29*(9), 1249-1254.

Wolf, S., Teitge, J., Mielke, J., Schütze, F., & Jaeger, C. (2021). The European Green Deal—more than climate neutrality. *Intereconomics*, *56*(2), 99-107.

Wooldridge, J. M. (2015). *Introductory econometrics: A modern approach*. Cengage learning.

Wu, X., Zhang, C., & Du, W. (2021). An analysis on the crisis of “chips shortage” in automobile industry——based on the double influence of COVID-19 and trade friction. In *Journal of Physics: Conference Series* (Vol. 1971, No. 1, p. 012100). IOP Publishing.

Zhao, B. (2017). Web scraping. *Encyclopedia of big data*, 1-3.