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Automobile industry and smart products: an Hedonic Price Model analysis

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Abstract

The automotive industry, in recent years, is facing a phenomenon of digital revolution. Since the advent of IT, digitalization has influenced various industries, modifying processes, products and business models related to them. The aim of this study is to investigate whether there is a positive correlation between the characteristics that make today's car a digital and smart product and the value perceived by the consumer.

The work is structured in five chapters. In the first one, a clear definition of digitization and analogous terms is given. After this, the unconventional changes that this form of transformation can deliver are observed with the aid of some examples. The focus shifts then to the automotive industry that, even though historically characterized by a physical product, is also facing a digital transformation driven mainly by market needs and new regulations. Then, the primary capabilities that make the automobile a smart and related product are listed with a brief description of the technologies that allow its implementation. Lastly, a number of the movements taken by leading groups in the sector and possible entrants are reported.

Chapter 2 presents an assessment of the scientific literature associated with the Hedonic Pricing Model, specifically with reference to applications in the automotive industry. Fundamental hypotheses and main mathematical models used in literature are highlighted.

After specifying the model, in the next chapter, the hypothesis object of this work and the relative models are presented. Also, information about the data

gathered are provided, concerning both the collection methodology and about the variable encoding.

Chapter 4 reviews the effects of the analyses accomplished to verify the hypotheses set out in the previous chapter. Descriptive statistics about the variables concerned are provided. Consequently, outlier identification process is described. Finally the regression analysis is performed and its results are shown, together with a robustness check and remarks about the regression coefficients obtained.

Last chapter reports the final considerations about the study carried out. Also, the limits of the work and suggestion for future research are furnished.

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Acronyms

LDWS

Lane departure warning system

AEB

Automatic emergency brake

IT

Information Technology

SMACIT

Social, mobile, analytics, cloud, and Internet of Things technologies

OEMs

Original equipment manufacturers

EV

Electric vehicle

ABS

Anti-lock braking system

HEV

Hybrid electric vehicles

PHEV

Plug-in hybrid electric vehicles

BEV

Battery electric vehicle

ICE

Internal combustion engine

ADAS

Avanced driver assistance systems

IaaS

Infrastructure as a service

PaaS

Platform as a service

SaaS

Software as a service

SWOT

Strength, weaknesses, opportunities and threats

NFT

Non fungible token

VIF

Variance inflation factor

IoT

Internet of Things

RFID

Radio Frequency Identification

NFC

Near Field Communication

QR

Quick Response

NIST

National Institute of Standards and Technology

ACC

Adaptive Cruise Control

PA

Park Assist

AI

Artificial Intelligence

ML

Machine Learning

Chapter 1

Digitalization and Digital Products

In the first chapter, a definition of the digitization of an Industry is given, followed by some examples that highlight the radical changes that this type of transformation can bring. After this, it is also highlighted that the automotive industry, historically characterized by a physical product, is undertaking a digital transition driven by both regulatory and market needs. At this point, the main features that make the car a smart and connected product are listed, together with a brief description of the technologies that allow its implementation. Finally, in light of the future prospects regarding the evolution of the market, some of the main actions taken by leading companies in the sector and by possible future entrants are reported.

1.1 Industry Digitization

The advent of information technologies since the Seventies has given way to a revolution that has affected more and more aspects within the life of industries. Their rapid evolution and diffusion on a global scale has challenged existing paradigms that have been renewed, modified or wiped out to make way for completely new scenarios. This trend has never stopped and further advances in the information technologies (IT), and in particular in the SMACIT (i.e. social, mobile, analytics, cloud, and Internet of Things) technologies [1] have led scholars to coin the term Fourth Industrial Revolution or Industry 4.0 [2]. Foundation of this phenomenon is the digitalization of products, production processes and business models. The term digitalization is defined by Riedl et al. [3] as “the process of introducing digital technologies, which essentially deal with changes caused by information technologies”; in this context technologies don’t have to be new, but should be applied in a way that they provide business improvement and value creation.

Digitalization is often overlapped with the term Digitization which has a more technical meaning, referring to the conversion of information from an analog to a digital storage medium [4]. Lastly, by digital transformation, we mean the deployment of digitalization and its results in term of disruptive value creation models. In fact, according to Vial, digital transformation is as "a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies” [5].

From these definitions we can see that digitalization has a clear bonding with strategic issues rather than describing a purely technical process. As stated by Ebert and Duarte, digital transformation "is about adopting disruptive technologies to increase productivity, value creation, and the social welfare" [6] and thus governments, industry representatives and managers have interest in pursuing digital strategies in order to implement new and innovative business models and to increase income generation, productivity and value addition in economy [6]. As a result, digitalization can help firms to adapt to fast paced changing market needs and to be able compete against threats coming from new scenarios.

As mentioned before, digital technologies can be implemented in order to improve three core aspects of a firm, namely production processes, business models and products. In the first case the objective is to build a Smart Factory, a plant where every machinery is connected to the Internet and is able to share information continuously and adjust every production parameter to improve flexibility and quality as well as report for possible failures and needed maintenance interventions. As stated by Radziwon et al. [7], a Smart Factory should be able to adapt to dynamic and rapidly changing boundary conditions.

On the other hand, digital transformation affects business models in four ways [8] by extending already existing features in the digital world (mainly in terms of connectivity and accessibility of information for both customers and firms), by revisioning or redesigning existing practices, creating new business opportunities or terminating obsolete activities.

Lastly, product digitalization deals with the creation of smart connected products. A smart connected product has three core elements, according to Porter and Heppelmann [9]: physical components, smart components and connectivity components. This three layers in the architecture of a product engage a virtuous cirlce of value improvement [9]: a smart component, such as a sensor, enables data collection from the physical component of the product which gives rise to the opportunity of improving the whole product performance as a whole or giving useful insights to the user; connectivity components, on the other hand, allows some smart components to exist outside the product itself.

Examples of industries affected by digitalization are the mining industry and the photography industry. Joy Global, for instance, is a company founded in 1884, specialized in manufacturing mining equipment such as continuous miners, haulage systems, shovels and so on [10]. Since the 1990s, Joy began selling smart products and providing after-sales services to increase their efficiency. Thanks to the combination of proprietary hardware and software, for Joy's customers the control of the equipment was gradually moved outside the tunnels where the extraction took place, significantly increasing safety for operators and technicians. These can in fact benefit from user interfaces that promptly report information regarding the operation of the various machinery and go underground only to solve specific maintenance issues. Gradually it was possible to create a control center outside the actual plant, thanks to the cable connection of all the equipment involved in the mining activities. Furthermore, starting from the collection of data from different mines, Joy has created a system that connects the control centers of the plants, providing its customers with a process of optimization service aimed at increasing performance and reducing of downtime. By developing its skills in the digital field, it was possible for Joy to modify its business model, initially based on the sale of products and spare parts, transforming it into one that contemplates the sale of products and services aimed at increasing the overall performance. In this way, Joy has differentiated itself from competitors, obtaining a position of competitive advantage on the market.

However, companies are not always able to exploit the possibilities provided by digital transformation. The case of Kodak is an example [11]. The company, since 1880, had conquered an absolute majority of the American market share in the sale of photographic products thanks to a strategy based on customer relations, high quality and low costs as well as a razor and blade sales model. However, when Sony began developing digital cameras, management's reaction turned out to be quite ineffective. Despite the undoubted R&D capabilities, in fact, a strong confirmation bias of middle managers hindered the adoption of innovative measures that required the development of capabilities not strictly linked to the chemical knowledge that resided within the organization. The difficulty in predicting the change in the photography market from analog to digital and the fear of cannibalizing the existing business led Kodak to incur in sustained economic losses and to lose its status as an absolute leader in the sector.

1.2 Car as a smart, connected product

As we stated before, digital transformation has interested also industries in which products cannot be completely digitised. Among the others, this work will focus on the automobile industry. In the last years, in fact, the amount of digitalization in vehicles has significantly increased, challenging manufacturers to find a balance between the new digital features and their core competences located in the physical world [8]. The phenomenon is driven by a major change in the social context. In fact, consumers ask for less polluting vehicles, more flexible ways to access to mobility, improved on-board connectivity and information, increased safety [12].

For the original equipment manufacturers (OEMs), different scenarios open up, each with its own threats and opportunities: national governments and supranational entities are imposing environmental and safety objectives to be achieved, under penalty of sanctions. In fact, although it is true that many countries support the low-emission vehicle market with different types of incentives to guide consumer choices, the European Commission has required car manufacturers to reduce CO_2 emissions by 15% by 2025 (compared to the values recorded in 2021) and the European Parliament's Environment Committee has questioned the possibility of imposing a minimum sales target for hybrid and electric vehicles of 20% by 2025 and 40% by 2030 [12].The spread of vehicles with electric (EV) motorization and the increase in electronic components will determine an increase in the demand for metals, such as copper, and rare-earth elements. This could generate some important issues for OEMs; for instance, the demand for copper in hybrid electric vehicles (HEV), plug in hybrid electric (PHEV) and battery electric vehicle (BEV) is increased by 17-40 Kg with respect to one alimented by a traditional internal combustion engine (ICE) [12]. The geopolitical distribution of this fundamental materials, often available in few countries, will have a significant impact for all OEMs who could have to face high prices due also to export caps and uncertainty of supply.

Some studies [13] on the automotive industry have tried to identify what condition must occur in order to achieve a high level of satisfaction for consumers and manufacturers; they do not lead to a unique combination of factors, but rather to various possible scenarios. However, the need to solve technical problems, provide updated regulations and develop new solutions in terms of services and business appears to be fundamental. To meet the aforementioned needs, OEMs are designing innovative vehicles. In fact, more and more cars equipped with electric or

Level	**Driver**	**Automation**
L0	Driver only	Driver continuously in control of speed and direction.
L1	Assisted	Driver continuously performs the longitudinal or lateral lateral dynamic driving.
L2	Partial Automation	Driver must monitor the dynamic driving task and the driving environment at all times.
L3	Conditional Automation	Driver does not need to monitor the dynamic driving task nor the driving environment at all times; must always be in a position to resume control.
L4	High Automation	Driver is not required during defined use case.
L5	Full Automation	System performs the lateral and longitudinal dynamic driving task in all situation encountered during the entire journey. No driver required.

Table 1.1: The six levels of automation for cars defined by the Society of Automotive Engineers.

hybrid motors are being placed on the market; the number of infotainment systems available to the driver and passengers and Advanced Driver Assistance Systems (ADAS) are increasing.

As for ADAS, some have been present on vehicles for several years now, while others are completely innovative. These systems allow to obtain different levels of automation; the Society of Automotive Engineers identifies six (Table 1.1).

Each degree in the scale corresponds to a greater autonomy of the machine, where the maximum describes a state of fully autonomous driving [14]. To these days, ADAS systems embedded in cars are classified as level 2+ on the aforementioned scale. A study [15] aimed at determining consumer confidence in ADAS has determined that the systems considered most useful are those that warn drivers of impending dangers and those that generally perform one task at a time, rather than more simultaneously. On the other hand, this trend is linked to the fact that the most complex systems are not yet well known by consumers, who instead have experience of the operation of those that have already been on the market for some time, such as the anti-lock braking system (ABS). The inclusion of these add-ons transforms the car into a product with important features that we can define as digital. From this perspective, the car can be seen now as a smart product and, as stated by Porter [9], it is able to perform different tasks, thank to four main capabilities:

1. Monitoring;
2. Control;
3. Optimization;
4. Autonomy.

The presence of integrated sensors inside the different components of the car allows the constant collection of relevant information regarding the state of the vehicle and the conditions of the surrounding environment; via the internet connection, moreover, salient information on traffic conditions and places of interest nearby is retrieved. This data is transmitted to the driver via displays, often touchscreens, inside the passenger compartment. Even the manufacturer, on the other hand, can also take advantage of the information collected, to develop new services to offer to the customer. The control of some features in the car is now possible through the smartphone, moreover, algorithms have direct control of some components, such as the headlights, where they adjust the intensity of the light beam in relation to external factors. Thanks to the features described above, it is possible for the OEM to optimize various processes, including, for instance, preventive maintenance for vital components of the product. Finally, as anticipated before, thanks to the combination of the new embedded digital features, today's vehicles, but even more in the future, will reach levels of autonomy such as to minimize human intervention.

The smart car thus makes it possible to create value also in the digital world, extending the existing BMs, that is, enriching the physical characteristics of the product; by reviewing current paradigms and creating new ones [8]. Thanks to the monitoring of information through sensors, it is possible to enrich the car's offer, which is no longer limited to being a simple means of locomotion, but an entity that interacts with the driver, enriching the driving experience. The possibility of connecting your mobile phone to the on-board system also increases the customization of the vehicle and contributes to increase the value perceived by the consumer compared to the physical product alone. For OEMs, the data collected from the vehicle is a potential source of revenue, as it can potentially be sold to third-party organizations interested in motorists' habits. Monitoring and control also make it possible to change the typical OEMs' business allowing them to move from a model of pure product sales with one-off payments to the sale of a service (mobility) through subscriptions and car sharing services. Furthermore, the ability to remotely control the car via the smartphone can be exploited by creating new services for the driver, perhaps by subscription, such as automatic emergency call in the event of an accident.

1.3 Enabling technologies

As mentioned above, digital transformation has involved many industries and businesses with heterogeneous characteristics. We also remind you that, for a product to be digitized, it is not necessary that all technologies involved are new [3]. However, at this point in the study, it seems necessary to understand what are the so-called enabling technologies that allowed the digitalization of the automobile. At first glance, it is clear that the technical skills necessary to master these technologies lie in the fields of electronic engineering, computer science and data science. The following list is not complete, given the large amount of systems and subsystems that make the car "smart". Furthermore, despite being presented separately, in general, it is the interaction of these technologies that triggers the digital evolution of the product.

1.3.1 5G

5G technology is perhaps one of the main drivers of digital transformation, both in the automotive sector and in others. In fact, connectivity is nowadays at the very heart of the digital revolution paradigm of virtually any kind of product or service.

5G (acronym for 5^{th} generation) is the technology on wich the new mobile network is based. This has twenty times higher performances than the previous 4G network (allowing a theoretical peak speed of 20 Gbps instead of the 4G's peak speed of only 1 Gbps [16]), thus allowing significantly faster and cheaper data downloads and uploads. The 5G network is designed to withstand a significant number of connections compared to the past [17] in view of the enormous increase in connections predicted for the next years. Its advanced bandwidth management capabilities guarantee, as mentioned above, a better management of high frequencies (and therefore high speeds), but also a wider coverage. All this with low costs, both in economic and energetic terms [17]. 5G networks are virtualized and based on software that resides primarily in the cloud [16]. Thanks to this new mobile network, in particular by virtue of the greater reliability of coverage and the ability to manage greater quantities of information quickly, the possibility of providing services related to connectivity for vehicles increases significantly. In light of this, 5G can be seen as one of the driving forces for the transformation of the car as a smart product and the business models connected to it.

1.3.2 Internet of Things

The expression Internet of Things (IoT) was born in 1999 as the title of a presentation for Procter & Gamble by Kevin Ashton, an English engineer active in the field of the study of RFID technology [18]. The idea behind the IoT is to make computers able to collect information from the physical world without human intervention. By providing the processors with "sensory" capabilities, they have the ability to constantly monitor the activities and events that take place in the surrounding environment. In general, the IoT can be defined as a network of objects of any kind, from vehicles to toys, from industrial machinery to everyday objects. These are all connected via the internet and are able to communicate and share information thanks to which it is possible to obtain a large number of services, such as the traceability of a package or the management of the heating system in a house [19]. To give life to the IoT network, technologies related to the various types of sensors are considered to be essential elements. Among these, we find Radio Frequency Identification (RFID), Near Field Communication (NFC) or that of Quick Response (QR) Codes [20].

Considering the case of interest of this work, that is the car industry, and in particular the car, this becomes "the object connected to the internet". The smart components integrated in it can be seen as the new sensory organs of the vehicle, which comes to life through the network with the aim of improving the consumer experience.

1.3.3 Cloud Computing

Cloud computing is a paradigm for the provision of IT services through the internet, The National Institute of Standards and Technology (NIST) is a US government agency active in the field of technology management. The NIST [21] definition of Cloud computing is widely accepted, indicating it as "[...] a model that allows widespread, convenient and on-demand network access to a shared set of configurable computing resources (for example networks, servers, storage, applications and services) that can be quickly made available and released with minimal management commitment and interaction with the service provider ". Cloud Computing has five essential characteristics that must be respected [21]:

1. On-demand self-service: each user can automatically supply the resources provided without requiring human intervention by the service provider;

2. Wide network access: the services are available online and easily accessible via heterogeneous platforms, such as personal computers, smartphones or tablets;

3. Shared resources: resources made available by the provider are assigned to different customers according to a multi-tenant model and are dynamically allocated based on demand;

4. Elasticity: resources can be rapidly scaled, automatically increasing or decreasing in order to be constantly adapted to the needs of users;

5. Measured service: the use of resources is constantly measured and optimized, transparently for the user and provider

Clouds can be private, community, public or hybrid [21]. For the former, the infrastructure is used exclusively by a single organization, which may or may not own it. This type of cloud aims to maintain greater confidentiality and security of data. Community clouds are managed and used by a group of organizations that have common interests. The public ones are instead the most widespread and their use is allowed to any user. The latter are a combination of multiple infrastructures that can be either public, private or community. The architecture of a cloud environment is divided into four layers [22]. The first is that of hardware. It is usually implemented in data center and its task is the management of physical resources, including electricity and cooling systems. Next we find the virtualization or infrastructure level. In this way it is possible to provide each customer with a virtual machine with all the characteristics of a dedicated physical machine. The third layer is that of platform, whose purpose is to decrease the workload through APIs and application frameworks. The last level, at the top of the architectural hierarchy, is the application layer, that is, the one in which the applications used by the end customer are located. Each layer can be considered as a customer of the previous level, as well as a provider of services for the next one. IN fact, we can identify different types of services provided though the cloud model, depending on the depth that is allowed to be accessed in the architecture. Thus, we can distinguish different types of services:

- Software as a Service (SaaS): completely remotely executable software is made available to customers, in this case we are in the highest level, the application level;
- Platform as a Service (PaaS): allows developers to automatically exploit the large computing and storage resources made available for the creation of applications;
- Infrastructure as a Service (IaaS): Gives software developers direct control over compute and storage resources provided by a cloud. In this way, greater flexibility is obtained, at the cost of greater complexity to be able to take advantage of all the services of the cloud.

For the automotive industry, the possibility of making use of cloud services accessible through the internet opens up new scenarios as regards the quantity and quality of software services available to the motorist. At the same time, OEMs can leverage offshoring of software and data infrastructure to achieve space and cost savings, as well as increase the customizability of the experience.

1.3.4 Radar and Lidar

Radar and Lidar are two of the technologies used to scan the surrounding environment. They behave like digital eyes, thus configuring themselves as real sensory organs that connect the physical world with that of the software.

Radar (a term that stands for Radio Detection and Ranging) is a technology that was developed for military purposes during World War II. The application of this technology in the automotive field sees the first experiments starting from the seventies ([23]). Before being able to reach the market, the applications developed during these studies clearly had to reach costs compatible with economic exploitation. Among the systems that make use of Radar technology, we find the Adaptive Cruise Control (ACC), the Park Assist system (PA) and the Autonomous Emergency Braking system (AEB) [24]. Radars used in the automobile field make use of different operating frequencies, depending on the use cases [24], however, recently, other technologies have also been developed to overcome some of the intrinsic limits of this technology.

Lidar (Light Detection and Ranging) systems use a powerful coherent light beam directed towards the area to be scanned [23]. A fraction of the optical power of the beam is reflected by the objects and is picked up by sensors, located, both coaxially and not, at the emitter. The most widely used optical sensors in the automotive industry are PIN-photo diodes and avalanche photo diodes [23]; the wavelength of the laser used is typically 0.850 µm or 0.905 µm [23]. Even for Lidar technology the costs are low enough nowadays to justify a large-scale use that allows economic benefits for manufacturers and OEMs, especially in the higher-end segments. In relation to Radar, the Lidar allows better performances in terms of angular resolution in the azimuthal plane, having a resolution capable of identifying objects even less than one degree away from each other [23]. However, for both technologies, and especially for the second, the weather conditions such as rain, snow and fog significantly worsen their performance, especially due to scattering. In fact, it is necessary to filter the data concerning the detection of solid objects, such as cars or pedestrians, and instead eliminate the detections concerning the reflection of the light beam by the drops of water suspended in the atmosphere [23]. This is necessary so that the recognition algorithms can carry out relevant detections and signal any dangers to the driver or even initiate corrective actions based on safety, avoiding "false positives".

The research applied to this kind of technologies is configured as fundamental, especially considering their importance relative to the automation systems that will lead in the near future to the achievement of autonomous driving.

1.3.5 Artificial Intelligence

For the digital transformation of the product, the software component is certainly the most important. The data collected through the sensors integrated in the various components of the car must be suitably filtered (as in the example presented in the previous subsection) and then processed. In order to perform these tasks, Artificial Intelligence (AI) and Machine Learning Algorithms (ML) are of fundamental importance.

Moujahid et al. [25] offer a review of the various types of ML algorithms used in the automotive sector. First of all, it is appropriate to distinguish the different types of existing algorithms and their features:

- Supervised Learning: these are algorithms based on the definition of models capable of predicting the outcome based on historical data, creating a correlation between combinations of inputs and related outputs;
- Deep Learning: They need large amounts of data for training and computing skills. They are characterized by different layers, where the first is called the input layer and the last the output layer;
- Reinforcement Learning: are algorithms modeled according to Markov decision processes where an agent acts within an environment obtaining rewards for obtaining the desired results;

- Unsupervised Learning: in this type of algorithm the goal is to structure the dataset and obtain an unknown output value from it.

In the same article [25] there are also several examples of the possible applications of the ML principles in the smart car. Supervised Learning-based algorithms can be used, for instance, to develop systems capable of making mandatory lane changes, as highlighted by Y.Hou [26]. Regarding Deep Learning, multi-layer neural networks can be used to develop collision warning systems in real time. Reinforcement learning, on the other hand, is applied to solve complex decision making problems, such as those that arise in particular traffic conditions. Finally, Unsupervised Learning can be used to determine the optimal speed of a car based on environmental conditions. The examples given here are limited; for a more in-depth view, the above mentioned article [25] and its bibliography could be useful.

1.4 The Industry Structure

The adoption of the technologies described in paragraph three of this chapter can cause a radical change in the environment of the automotive industry. Due to their nature, radically different from that of the core competencies of OEMs, there are various threats that arise in the future for incumbents. It is also true that there are just as many opportunities for companies that have many years of experience in the aforementioned fields of interest.

Before discussing the possible effects related to the actions of the various actors involved in the digitalization of mobility, it is necessary to describe which components regulate competition within an industry. To do this it is possible to use the model of the Five Forces of Competition developed by Porter [27]. The five forces identified by Porter are sources of competitive pressure for companies; each of them has a strength relative to structural variables typical of the industry itself (Figure 1.1).

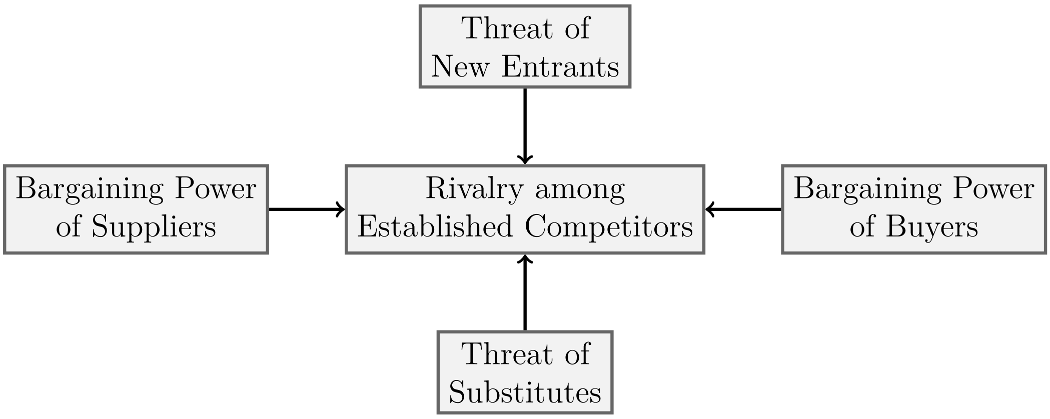

Figure 1.1: The Five Forces of Competition according to Porter

In the context of the digital revolution, however, their relationship can be subject to radical reversals, eroding industry profitability for incumbents. The framework includes:

1. Competition from entrants that is the one performed by new firms or ones that try to diversify their operations. Usually, incumbents can discourage this type of threat by investing large amounts of capital, exploiting economies of scale, by announcing price wars (according to Nash theory of Games) and by relying on established customers and suppliers;

2. Competition from established rivals is the one based on product differentiation, and cost competition. Usually in relatively small markets that can be seen as

oligopolies firms collude on prices which are set above the competitive level;

3. Competition from substitutes is the one coming from similar products and depends on consumer's price sensitivity;

4. Power of suppliers is linked to the possibility of firms to easily switch from one supplier to another. If a supplier produces commodities its power will be significantly lower than the one of a firm producing rather unique products;

5. Power of buyers is similar to power of suppliers; it is also affected by accessibility of information about prices and features in products and sensitivity to prices.

Usually, when applying this framework we refer to an Industry's value chain. However, in considering today's automotive industry in the perspective of the digital revolution, it may be useful to refer to a value network. Riasawon et al. in a study about the structure of automotive industry [28] identified various "internal" and "external" actors with respect to the traditional automotive industry by reconstructing their relationships through the definition of the flows of money, services, products and information that are exchanged between them. The results show three clusters representing the traditional car industry, alternative mobility service providers and cloud service providers; in addition, also suppliers of disruptive technology, online payment service providers, automotive service providers as well as consumers are involved (Figure 1.2). Within the first cluster there are OEMs and suppliers of the first, second and third Tier, as well as spare parts dealers. In the second cluster, public transport companies and alternative mobility service providers stand out, together with mobility service aggregators. In the third cluster we see the cloud service providers, in the three forms: IaaS providers, PaaS providers and SaaS providers.

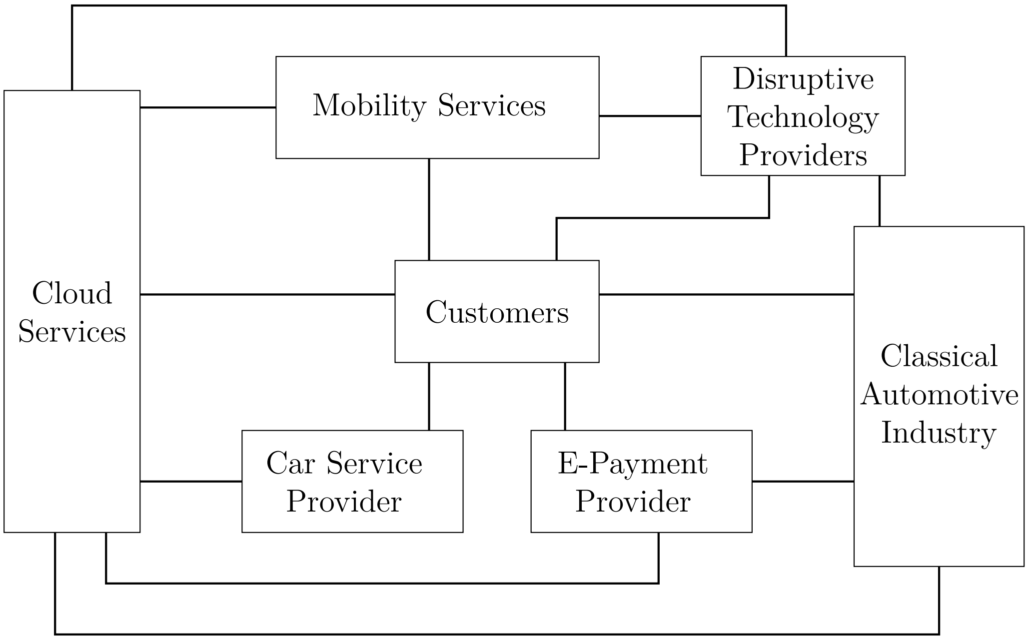

Figure 1.2: Simplified Automobile Industry Value Network

After having described the actors involved, it is therefore possible to analyze the contribution of the most relevant ones in modifying the structure of the automotive industry in light of the forces they can exert on competition.It is important to underline that, in the real world, the same company could belong to several categories, having already diversified its operations, and therefore exert different competitive forces.

1.4.1 Original Equipment Manufacturers

OEMs have so far been the major players in the automotive industry. Being in a position of advantage over suppliers and privileged towards consumers, they were the main providers of mobility services. In the context of this study, the digitalization of the car exerts an important force as it allows them to differentiate even more their products from that of competitors. Furthermore, given that in general the unit cost of many digital systems is relatively low, the final price for customers is not increased drastically for those segments that tend to compete on price. For OEMs it is essential to keep pace with their direct competitors (or to anticipate them) in order to gain reputation and market share and increase their profitability.

1.4.2 Suppliers

Automotive industry is characterized by three Tiers of suppliers. OEMs buy physical components and software from Tier 1s, which in contrast have subcontracts with Tier 2 and Tier 3s. Tier 1 suppliers supply about 85% of a car's components. In many cases products and semi-finished products from this category are considered commodities and their influence on the industry is relatively low. To increase their bargaining power it is important to develop high-tech products and to attempt to set de facto standards for the entire industry.

1.4.3 Alternative Mobility Service Providers

Mobility service providers include all the realities that offer consumers the possibility to access urban and inter-urban transport without the need to purchase a vehicle. These include car sharing services, both private and commercial, car rental services, public transport and platforms that allow the provision of these services. Digital transformation allows the actors in this group to create a serious threat to OEMs in terms of substitute products. In fact, the possibility of including remote control systems on cars and the development of ad hoc software and platforms has greatly simplified the procedures for accessing these services. In addition, more and more consumers consider the costs of managing and maintaining a car too high with respect to their needs. This is true especially in large-urbanization scenarios where consumers may prefer alternative mobility solutions. Finally, the increasing automation of the vehicles could attract occasional and less experienced drivers towards pay-per-use solutions of this kind.

1.4.4 Cloud Service Providers

As stated before, Cloud Service Providers supply three services, namely Infrastructures, Platforms and Software. Through these different services, computing resources, storage resources and applications are provided to customers. The core capabilities of these companies are related to the storage, management and analysis of data. In the digital world, the ability to analyze large amounts of data (Big Data Analytics) is essential to extract information of the highest value. Furthermore, many companies that develop software, using the services Cloud Providers offer, could make them de facto owners of the data themselves, depending on the contractual clauses. In the context of the digital revolution being covered by this work, some companies belonging to this cluster could diversify their operations, presenting themselves as suppliers of alternative mobility services or even threaten entry into vehicle production. The latter scenario is all the more realistic as the level of automation - and consequently the importance of the knowledge residing in these organizations - increases.

1.4.5 Suppliers of Disruptive Technologies

Suppliers of Disruptive Technologies are those who offer products characterized by disruptive innovations. Their expertise is of strategic importance for the industry which, in the long run, will adopt these new technologies on a large scale. From the point of view of competition, these companies can exert a strong bargaining power towards OEMs (which are their customers), precisely by virtue of their capabilities and know-how that often derive from decades of experience in the field of interest. The collaboration between OEMs and Suppliers of Disruptive Technologies can give rise to a lock-in effect, in which it would be the latter who would have greater bargaining power by virtue of the uniqueness of their hardware and software. Lastly, also suppliers of Disruptive Technologies could threaten entry into vehicle production and alternative mobility services (thus competing as substitutes products).

1.4.6 Consumers

Consumers do not correspond to motorists in the strict sense. In fact, the need for mobility, as mentioned above, can be satisfied through the purchase of a car, through the use of public transport or through short and long-term rental services and car sharing. Thanks to the increase in the offer if mobility services in general and the possibility of managing transactions in a simplified way (via E-Payment services), the bargaining power of consumers is strengthening. The possibility of easily obtaining information about the products offered by the various companies and therefore of optimizing the utility obtained through the choice also contributes to this. Finally, the ability to access pay-per-use payment schemes can prove to be an opportunity for all those who are not willing to invest in buying a product.

1.5 Digital Strategies

In the previous sections, the concepts of digitalization of an industry and the characteristics of smart products within the renew automotive industry were introduced; finally, the possible effects of digital transformation on the competitive structure of the automotive industry were described using Porter's five forces framework. At this point it is appropriate to talk about the digital strategies implemented by companies to enhance and respond to the changes described above. Chanias et al. in a 2016 study [29] analyzed the mechanisms that lead to the creation of the digital strategies within the European automotive industry. The results surprisingly indicate that often in the automotive companies it is the various divisions that autonomously give life to digitalization of products or businesses via a bottom-up process. It is only at a later time that high-level managers act by aggregating the various innovative trends within the organization to pursue a common and consistent digital strategy. The analysis of the triggering event [29] is also of interest: in all three cases among the causes related to the initiation of digital strategies there are the threat of entry into the market of new players, the change in customer needs and the threat of commoditization. This latter result appears to be consistent with the general environment depicted up to now.

The digital strategies implemented can challenge long-standing paradigms, such as the trend by OEMs to resort to outsourcing with regard to the development of software and other IT services. However, the large amount of data generated (by smart factories, products and new businesses) and the consequent demand for experts in the IT field seems to recall these activities back inside the companies' perimeter. A study carried out in Germany [4] shows that, for the backsourcing of

IT services to become a trend, the fundamental requirements are being met. It is important to note that, just as the outsourcing does not find unanimous scientific evidence regarding its effectiveness in all possible scenarios, even in the case of backsourcing a bandwagon effect could occur [4], resulting in an unprofitable choice for some companies. Apart from the effectiveness of this type of measures, which should be verified through careful case-by-case evaluations, the centrality of the data and the definition of common architectures within the various functions and divisions of the OEMs appears to be of vital importance for a successful digital transformation [30].

To have a clearer -albeit incomplete- picture of the digital strategies implemented by companies, here are some qualitative examples of the actions taken and planned by them. It is interesting to note that some companies are already diversifying their operations, entering new businesses or by signing partnerships.

1.5.1 Mercedes-Benz Group AG

The Mercedes-Benz Group AG has recently embarked on a radical transformation regarding the perception of the brand in a sustainable and digital key. Since 1st February 2022, the historic name Daimler Group AG has been changed to Mercedes-Benz Group AG [31]. The name change has a particularly symbolic and strategic value, as stated by Ola Källenius (chairman of the group's board of directors) [31]: "The new identity further underlines our strategic focus. We want to keep our promises and pick up the legacy of our founding fathers by trying to become leaders in mobility and software related to the automotive world". At the same time, an industrial plan worth 60 billion euros was announced for the five-year period 2022-2026 [32]. Despite a general reduction in investments, expenses for digitalization, electric transition and autonomous driving will not be reduced. Other important strategic actions concern the transition to online direct sales models and the sale of digital services. In this regard, the CEO of Mercedes Italy, Radek Jelinek [32], stated that a proprietary operating system will be launched on Mercedes-branded models by 2024 in order to better integrate digital platforms and artificial intelligence functions present on vehicles. The strategic implication is the possibility of quickly and effectively opening new digital business channels in direct communication with the customer, also thanks to over-the-air updates.

The range of services that will be implemented also includes the new frontier of in-car payments. Thanks to a partnership with Visa, Mercedes-Benz AG has in fact developed a system management system for online payments which allows you to finalize purchases without the need to use your smartphone for further identification [33]. The system will be integrated into the Mercedes Pay software. Equally interesting is the announcement of the Smart brand (owned by Mercedes-Benz AG) that has decided not to provide a mirroring interface for Android or Apple operating systems in its new model, smart #1 [34]. The decision to develop its own operating system (connected to a Microsoft Cloud and installed on an on-board computer equipped with a Qualcomm Snapdragon SA8155P processor) aims to regain control of the digital component of the car. Finally, through a joint venture with BMW, Mercedes has created the mobility service company FreeNow, which acts as a platform for integrating the various public and private services available in the main Italian cities [35].

1.5.2 Stellantis

Stellantis is one of the world's largest groups in the production of vehicles and provider of mobility services whose strategic focus is the electrification of the fleet of its 14 brands, the sustainability of its operations and the development of new software services [36]. On March 1st 2022, the long-term strategic plan Dare Forward 2030 was revealed to shareholders with the aim of reducing carbon emissions and pursuing a strategy of creating value for all stakeholders. The plan is based on four pillars [37]:

1. Ethics;
2. Technology;
3. Value;
4. Finance.

To purse its objectives in the field of digital products, Stellantis has signed an agreement with the leading manufacturer of microchips Qualcomm to use the Snapdragon Digital Chassis, a hardware system connected to the cloud that implements, among other things, connectivity and vechicle driving assistance [38]. Thanks to the IT resources provided through the cloud it will be possible to implement the Smart Cockpit. The latter was developed by the joint venture between Stellantis and Foxconn in collaboration with Amazon Web Services and the Amazon Devices and Amazon Last Mile divisions [39]. As for the digital services present on the group's cars, it is notheworthy the collaboration between Alfa Romeo and Amazon. In fact, the new hybrid SUV Tonal will integrate the functions of the Alexa voice assistant and will allow an innovative delivery system, directly into the trunk of the car [40]. Also of a certain interest is the innovative use of non fungible tokens (NFT) based on the blockchain technology [41]. Thanks to this token, the vehicle owner will be able to allow the collection of information related to the life cycle of the car such as kilometers traveled and maintenance events, which will then be available through a mobile app. By virtue of the non-falsifiability of the certificate, this service can be exploited by the owner to guarantee the state of the car in the second-hand market, for instance.

To meet the new digital needs, Stellantis also announced a partnership with Palantir Technologies Inc. for using the Foundry [42] operating system. The goal is to implement this system in all divisions of the organization to accelerate digital transformation through the integration of siloed data sources in a common environment. In terms of mobility services, the company Free2Move has signed an agreement for the acquisition of Share Now (previously purchased by BMW and Mercedes-Benz) to increase its presence in major European cities and increase its vehicle fleet with the aim of increasing revenues from the car sharing sector to reach 2.8 billion and active users up to 15 million by 2030 [43]. On the same level is also the acquisition, always by Free2Move, of Opel Rent. Finally, Dare Forward 2030 also gave birth to Stellantis Venture, announcing investments in start-ups and innovative companies for 300 million euros to capture further innovations regarding the mobility, marketing, sale and finance of vehicles [44].

1.5.3 Volkswagen AG

Volkswagen AG is one of the largest automakers by sales worldwide. It owns several brands, among which we have Volkswagen, Audi, Porsche, Seat, Bentley and so on. In the past year Volkswagen AG has seen a redistribution of tasks in the top management levels and has declared an investment plan of 159 billion euros, of which the 56% will be allocated to the research of new technologies [45]. These investments were foreseen by the "New Auto" corporate strategic plan. This envisages an evolution of mobility drastically directed towards electric vehicles and an increasingly decisive role of the software component (crucial for the sale of digital services) [46]. For the development of the software component, the company Cariad aims to develop a single digital platform common to the various brands of the group to release over-the-air updates and new infotainment systems. This infrastructure will gradually allow for the development of new data-based business models and will prepare the Volkswagen AG's fleet for level 4 autonomous driving (see table 1.1). In addition, the Big Loop process will make it possible to expand the life cycle of the products.

The New Auto strategy leads the Volkswagen group to address issues related to the procurement of microchips and the development of innovative batteries. A joint venture will be set up with Umicore to ensure the supply of cathode materials needed to increase the production capacity of the gigafactories [47]. With 24M Technologies a partnership was signed to develop an innovative process in the production of batteries to obtain significant savings on investments and more efficient recycling, in addition to the reduction of the carbon footprint related to production [47]. Lastly, a contract with Vulcan Energy Resources provides for the supply of lithium hydroxide for five years to ensure the group will be allowed to directly produce battery cells in Europe.

In terms of alternative mobility, Volkswagen AG has launched a completely green ridesharing and vehicle sharing service on the island of Astypalea in collaboration with the Greek government, respectively ASTYBUS ans ASTYGO [48]. To meet the needs of customers, moreover, Volkswagen has developed an online service that allows the configuration of the vehicle, the definition of leasing options, the digital authentication of the consumer and the conclusion of the contract [49]. This innovation is configured as an extension of the current business model as it was not intended as a replacement of the role of the dealers [49]. Volkswagen AG has also created an account on the popular social network TikTok to reach new generations of customers and make them aware of the group's strategic choices in the field of sustainability and digitalization [50]. The presence on European, American and Chinese social networks aims to increase interaction with customers in these three important basins though infotainment and the sharing of original contents [50].

Finally, the Volkswagen Group has also launched a venture capital fund, allocating 300 million euros to finance innovative start-ups in the field of renewable energy in order to create synergies with its operation but also to develop new business models starting from the partnerships that will be signed [51].

Chapter 2

Hedonic Price Model Literature Review

Chapter 2 presents a review of the scientific literature related to the Hedonic Pricing Model, in particular with regard to applications in the automotive field. The fundamental hypotheses, the limits of applicability and the main mathematical models used in the literature are also presented.

2.1 Theoretical framework

The Hedonic Price Model was born during the 1930s from the studies carried out by Court and published in 1939 [52]. During those years, in the field of econometrics, the need arose to develop new methods to compare the prices of products characterized by the assembly of hundreds of components, with different designs and rapidly evolving [52]. Precisely for Court, in fact: "*No valid price comparisons can be made without [...]definition of the articles priced in terms of* *their useful and desirable physical characteristics.*". To take into account these characteristics, a multiple regression analysis is proposed using the price of the various goods as a dependent variable and the corresponding physical characteristics are considered as independent variables.

However, for about twenty years, Court's studies found no success in the scientific community and were not applied extensively [53]. The causes of the delay in the application of the hedonic model, according to Goodman, are essentially attributable to three factors [53]:

1. The focus of the economists was centered on aggregate macroeconomic quantities, resulting in a lack of data suitable for carrying out a hedonic regression;
2. The data collection itself was made difficult by the fact that the information was generally fragmented and not digitized;
3. The computation of regressions with dozens of variables was complex and expensive and often not supported by sufficiently powerful electronic calculators.

However, at the turn of the sixties and seventies, thanks to the studies of Griliches, Rosen and others, there is a renewed interest in the model. In his 1974 study [54], Rosen states that "*product prices and the amounts of characteristics associated with each good define a set of implicit or hedonic prices*". Hedonic prices are therefore the implicit prices related to the various attributes possessed by a good that reveal the utility enjoyed by the consumer of those goods. The term "hedonic" derives from the Greek word *hēdonikos* which means pleasurable. Rosen [54] proposes a two-step methodology for obtaining demand curves for the individual attributes possessed by an asset. In Rosen's model, therefore, each good is characterized by n characteristics. Using his notation, these can be collected in a vector:

$$z = (z_1, z_2, ..., z_n) \quad (2.1)$$

Also, "*goods are valued for their utility-bearing attributes or characteristics*". Therefore, the price p is a function of the vector defined in equation 2.1:

$$p(z) = p(z_1, z_2, ..., z_n) \quad (2.2)$$

Rosen states that the hedonic price function, in conditions of short-run equilibrium of the market, corresponds to the locus of the points where the marginal functions of supply and demand are equal. Therefore, "*in equilibrium, a buyer and seller are perfectly matched when their respective value and offer functions "kiss" each other, with the common gradient at that point given by the gradient of the market clearing implicit price function p(z)*". The partial derivatives of the function with respect to the *i-th* component, $\frac{\delta p_z}{z_i}$ represent the implicit price of each component. To estimate demand curves for attributes, the second step foresees the use of implicit prices obtained through regression. In a subsequent study, in collaboration with Brown [55], however, Rosen defines further hypotheses necessary so that the second stage of his methodology does not replicate the information obtained from the regression analysis.

The hedonic pricing model, as anticipated, is used by many scholars in their price analysis in industries characterized by multi-character products. Among the most notable areas are real estate market (notable examples are the works by Richardson et al. 1974 [56] and Parsons 1990 [57]) and the automotive industry.

Among the most authoritative studies concerning the automobile product, we find those carried out by Zvi Griliches starting from 1961. The objective of these studies is to determine correction factors for the price indexes of automobiles in the United States that take into account change in the quality (characteristics) that characterize the product ([58],[59]). To do this, information about the main models on the market in the US is collected. In particular, the prices and the main physical characteristics of the cars are recorded, including horsepower, weight and length. The prices, which represent the dependent variable in the regression performed by Griliches (as well as the other variables) are those obtained from the price lists of new cars and not those corresponding to the transactions actually carried out, for example, on the second-hand market. According to Griliches [58] "*one of the problems associated with the use of list prices in this study is the extent to which they may just represent pricing mistakes by manufacturers at some point in time*" which would determine a difference between the supply and demand curves (these would imply a negation of the short-run market equilibrium). The functional form chosen in these studies is semilogarithmic. This means that the logarithm of the prices is related with the absolute values assumed by the other characteristics. The advantage of this functional form for *p(z)* is that the generic regression coefficient can be interpreted as the percentage increase (or decrease in case of negative sign) of the price as the quantity of the corresponding independent variable increases, keeping the others constant.

In the next section, however, the other possible functional forms and some criteria that can be used to determine which is the best model to use in the various cases will be presented.

2.2 Functional forms and interpretation

In literature there are several examples of how the hedonic price model can present different functional forms to represent the relationship among the *p(z)* function of the price and the z vector of characteristics. Among the most used are the aforementioned semi-logarithmic, the linear (where no transformations are made on either the dependent variable or the independent variables) and the logarithmic (which provides the relationship between the logarithm of the dependent variable and the logarithm of the independent variables).

In a 1981 paper by Halvorsen and Pollakowski, a functional form that expresses the hedonic price function in the most general way is presented [60]. By formulating different hypotheses and assigning the appropriate values to the coefficients present in the equation from time to time, it is possible to trace all the specific functional forms, including those mentioned above [60].

Anyway, before presenting the mathematical model proposed by Halvorsen and Pollakowski, it should be emphasized that their work is also based on the work by Box and Cox [61] who defined the homonymous transform in 1964. For a generic variable Y the Box-Cox transform $Y^{(\lambda)}$ can be defined as follows:

$$Y^{(\lambda)} = \begin{cases} \frac{(Y^{\lambda}-1)}{\lambda}, & \text{if } \lambda \neq 0 \\ \ln Y, & \text{if } \lambda = 0 \end{cases} \tag{2.3}$$

The Box-Cox transform function is defined for non-zero values of λ. In addition, at the limit for $\lambda \to 0$ the function of the Y^{λ} transform tends to $\ln Y$. For λ equal to one, the transform returns a linear function with respect to Y. In general, moreover, the value of Y must be strictly positive for the function to be defined for every λ value. Downstream of this premise, therefore, the general model proposed by Halvorsen and Pollakowski [60] is:

$$P^{(\theta)} = \alpha_0 + \sum_{i=1}^{m} \alpha_i Z_i^{(\lambda)} + \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{m} \gamma_{i,j} Z_i^{(\lambda)} Z_j^{(\lambda)} \qquad (2.4)$$

Where P denotes the price, Z_i the attributes and $\gamma_{i,j} = \gamma_{j,i}$. Moreover, $P^{(\theta)}$ and $Z_i^{(\lambda)}$ are Box-Cox transformations. To choose the most suitable functional form "*a test of whether a particular functional form is acceptable is performed by testing the null hypothesis that the parameters of the hedonic equation satisfy the relevant restrictions*". It is possible to notice that, by setting $\theta = 0$, $\lambda = 1$ and $\gamma_{i,j} = 0$ for each i, j, we are reduced to the semi-logarithmic form.

Despite the indications of Halvorsen and Pollakowski, anyway, as we will see, the data collected and the variables encoded in this study do not fit well with the Box-Cox transform and consequently with formula 2.4, as they violate some of the conditions set out above. Although there are techniques to circumvent this obstacle, the necessary manipulations of the data would lead to results that are difficult to read and, therefore, of relatively low utility. For this reason, the functional form used will be the semi-logarithmic one, proposed, among others, by Griliches during his aforementioned studies.

Finally, another study by Halvorsen, this time in collaboration with Palmquist [62] provides a more correct interpretation of the coefficients of linear regression with regard to dummy variables (variables encoded as either 0 or 1). Halvorsen and Palmquist demonstrated, in fact, that for dummy variables the percentage effect on the dependent variable is not equivalent to the value assumed by the regression coefficient, but can be calculated using the formula:

$$\frac{\partial y}{y_i} = (e^{\alpha_i} - 1) \qquad (2.5)$$

Where $\frac{\partial y}{y_i}$ is the rate of percentage change of the independent variable with respect to the *i-th* independent variable and α_i is the respective regression coefficient.

2.3 Automotive sector applications

The applications of the hedonic model in the automotive field are among the most frequent. In fact, as anticipated in the beginning of this chapter, the first field in which Court applied the hedonic model in 1939 [52] is precisely that of the automobile. The subsequent studies that brought the model to know its current fame and diffusion (among which we find the aforementioned Rosen 1974 [54] and Griliches 1961 [58] and 1964 [59]) also had as their object of study the automotive industry. To date, there are countless works that combine this technique and the world of the car. Below, a brief digression is presented. It outlines how, over the years, the hedonic model has been exploited by scholars to test hypotheses of a different nature.

In the 1980s, following two major shocks in oil price, the attention of the scholars shifted towards the efficiency of motor vehicles. In particular, Goodman's 1983 study [63] and Atkinson ans Halvorsen's 1984 study [64] can be recalled. The first investigated the willingness to pay of consumers for cars with better performances in terms of "miles per gallon", based on the values of the "Red Book" [63] (a specialized magazine that reported the official evaluations of used cars). The second, in a similar way, investigated the relationship between the increase in the price of gasoline and the demand for car attributes, particularly with respect to fuel efficiency, using a method aimed at decreasing multicollinearity of the analysis [64].

On the other hand, many studies focus on determining and correcting the price indices for cars. For example, the studies by Izquierdo et Al. in 2001 [65] and Matas and Raymond in 2009 [66] focus on the relationship between changes in car prices on the market and the change in quality over the same period, measured though the change in the main attributes that characterize, in general, passenger vehicles. A similar study by Reis and Silva [67], aimed at relating the prices of cars in Portugal and their quality attributes, concludes that there is an overestimation of the consumer price index linked precisely to the fact that variations in quality are not considered.

Andersson's work "*The Value of Safety as Revealed in the Swedish Car Market: An Application of the Hedonic Pricing Approach*" aims instead to verify whether Swedish consumers pay a premium for driving cars that are considered to be safer [68]. Erdem and Şentürk instead research the determinants of the price of used cars in Turkey in their 2009 study using three different models, one semi-logarithmic, one logarithmic and one involving a Box-Cox transformation [69]. The results obtained show that the year of production of the car, as expected, has a significant influence on the price. Finally, a 2015 study by Prieto et Al. [70] aims to verify the implications of prospect's theory on the used car market through a hedonic regression. The results of the study show that consumers are risk averse when car reliability is higher than the average value, while when this is lower than the reference value, they are risk seeking.

Chapter 3

Research Hypothesis and adopted Models

In this chapter the two research questions object of this work and the related mathematical models that will be used in the analysis are exposed. The ultimate goal is to determine whether the impact of automobile digitalization has a positive effect on its value. As reported in the literature, the hedonic price model is optimal for obtaining information on products that possess many relevant attributes in order to establish their total value. The car responds perfectly to these characteristics and it is for this reason that both hypotheses have been tested using models of this type. In the last sections of the chapter, statistics regarding the variables taken into consideration and the methodology with which the data were collected are provided.

3.1 First hypothesis

The first hypothesis is based on the idea that the systems that make the car a smart, connected product inherently increase its value. We can therefore ask if:

"The presence of each system integrated in the car in order to make it a smart connected product is positively correlated with its value."

The value of the car is calculated as:

$$Value = ln(Price) \quad (3.1)$$

The model adopted to test this hypothesis is a log-linear relationship between the value of the car and its attributes. It can be expressed as follows:

$$Value = \beta_0 + \sum_{i=1}^{n} \beta_{AD,n} AD_n + \sum_{j=1}^{m} \beta_{IN,m} IN_m + \sum_{k=1}^{p} \beta_{M,p} M_p + \sum_{w=1}^{q} \beta_{V,q} V_q \quad (3.2)$$

Where $\mathrm{AD_n}$ are the *n* variables that describe the presence of ADAS systems in the car, $\mathrm{IN_m}$ are the *m* variables that indicate the presence of systems related to infotainment, $\mathrm{M_p}$ are the *p* variables that describe the attributes of the model under consideration and $\mathrm{V_q}$ are the *q* attributes that describe the specific version. Accordingly:

- $\beta_{AD,n}$ are the regression coefficients relative to ADAS;
- $\beta_{IN,m}$ are the regression coefficients for digital and infotainment systems;
- $\beta_{M,p}$ are the regression coefficients relative to the model attributes;
- $\beta_{V,q}$ are the regression coefficients relating to the attributes of the single version;

- β_0 is the constant term.

A more accurate description of all the variables involved in the model will be given in section 3.4.

3.2 Second hypothesis

The second hypothesis, on the other hand, is less restrictive and aims to capture the effect of ADAS and advanced connectivity features in an aggregate manner. The test of this hypothesis is interesting because the presence of many disaggregated indicators can give rise to results that are difficult to interpret from a broader perspective. Therefore the second hypothesis can be formulated in this way:

"The value of a car is positively correlated with the presence of features and optionals that increase the degree of automation and that increase connectivity and the possibility to use digital services"

Also in this case the value is calculated as in equation 3.1 and the model is a log-linear relationship that links the value of the car to its characteristics:

$$Value = \beta_0 + \beta_1 Automation_{score} + \beta_2 DigitSer_{score} + \sum_{k=1}^{p} \beta_{M,p} M_p + \sum_{w=1}^{q} \beta_{V,q} V_q \quad (3.3)$$

In this second equation the term $\mathrm{Automation_{score}}$ represents an empirical index that assigns a score to each car relative to the quantity and complexity of driving assistance systems present onboard and β_1 is the relative regression coefficient; $\mathrm{DigitSer_{score}}$ represents a similar index that assigns a score for digital services and β_2 is its regression coefficient. The other terms that appear in the equation are the same as in equation 3.2 Also, the equations that allow the calculation of the

Engine Fuel	Number of observations	Percentage %
Gasoline	436	28,04%
Diesel	351	22,57%
Petrol Hybrid	271	17,43%
Rechargeable Hybrid	192	12,35%
Diesel Hybrid	172	11,06%
Electric	107	6,88%
LPG	19	1,22%
Methane	7	0,45%
Total	1555	100,00%

Table 3.1: Type of engines in data sample.

indices are reported in the section 3.4..

3.3 Data collection

The data was collected mainly using the information reported by the well-known specialist magazine "Al Volante" of March 2022. These were then compared with those on the monthly magazines "Quattroruote" and "L'Automobile". In order to respect the hypothesis of non-segmentation of the market required by the hedonic price model, the research was focused on models belonging to the SUV and crossover categories.

The car models examined are one hundred, among those belonging to forty brands of the main car manufacturers on a global scale. For each model, the different versions available on the market have been taken into consideration, differing from each other in terms of engine (see table 3.1) and standard optionals. Each version, moreover, a "full-optional" version has been included, where needed. The latter reports the presence of paid add-ons of interest for the research and the relative increase on the total price of the car. In this way, data on 1555 different vehicles were collected.

3.4 Variables description

This section describes the variables used in the two models and their coding. We can divide the variables into three sub-categories. The first consists of the dependent variable, the second of the explanatory variables and the third of the control variables. The three sub categories are all treated separately in the following sub-sections.

3.4.1 Dependent variable

The dependent variable of both models is the value of the car, calculated as in equation 3.1, i.e. as the natural logarithm of its price. From here on, therefore, it will be referred to as *ln_price*. This mathematical transformation allows to obtain a distribution of value closer to the normal (fig. 3.1). Furthermore, using the natural logarithm of the variable of interest, the coefficients related to the independent variables will give information about the percentage effects that these have on the dependent variable. The prices considered are the list prices obtained as mentioned in section 3.3 of this chapter, using information from specialized magazines in the sector. The decision to use list prices is dictated by the fact that, unlike other markets, such as the real estate or the second hand ones, the ex-dealer price is not subject to negotiation, thus reflecting that of transactions carried out.

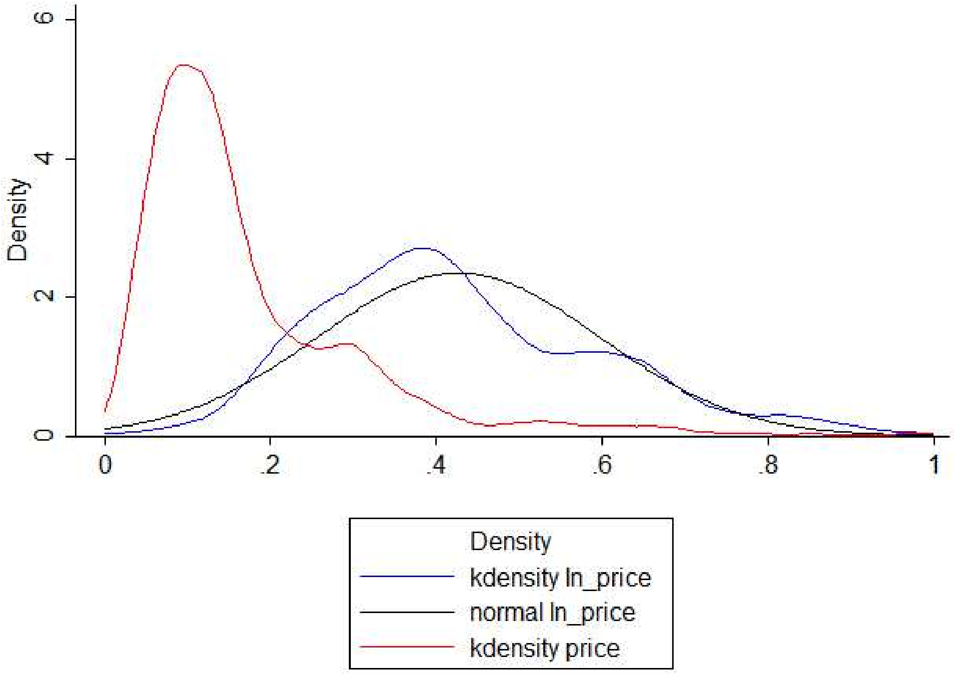

Figure 3.1: Price and ln_price distributions vs normal

3.4.2 Explanatory variables

The explanatory variables are different in the two models adopted to test the hypotheses object of this study. In the first model, twenty-three variables are taken into consideration, corresponding to as many systems that can be found on board the cars on the market. These are divided into two categories. The first refers to ADAS systems. Each variable indicates the presence or absence of the system, they have therefore been coded as dummy, as follows:

$$AD_n = \begin{cases} 1, & \text{if } AD_n \text{ is included} \\ 0, & \text{if } AD_n \text{ is not included} \end{cases} \tag{3.4}$$

The variables belonging to this group are n=13 and describe systems that provide driver assistance in different ways, with different levels of automation. Among these, three are responsible for parking assistance:

1. *camera* indicates the presence of front view and rear view cameras;

2. *sensors* indicates the presence of proximity sensors that help the driver during the parking maneuvers;

3. *pa* is an advanced system that exploits sensors and software to perform all the steering maneuvers; the driver controls the brake and and throttle pedals.

Four, on the other hand, assist the driver though warnings and danger signals, as well as providing information on the surrounding driving conditions:

1. *ahb* is the automatic high beam: thanks to light sensors the car is able to adjust the intensity of the headlights; when another vehicle comes from the opposite direction, the intensity is reduced;

2. *tsr* stands for traffic sign recognition and helps the driver to comply with traffic regulations such as the maximum speed allowed;

3. *bsm* is the blind spot monitoring that gives acoustic signals when the sensors detect an incoming vehicle behind during lane changes;

4. *dcm* or driver condition monitoring detects driver's fatigue thanks to facial recognition software and the detection of atypical behavior while driving.

Still others assist the driver in managing the lateral movements of the vehicle:

1. *ldws* gives the driver acoustic signals when unwanted lane changes are detected;

2. *lka* is a system that actively helps the driver in keeping the lane, also taking over the steering maneuvers.

Finally, the last four systems carry out more or less complex controls of the vehicle speed, in different conditions:

1. *hdc* is the hill descent control which performs the speed control downhill;

2. *hhc* is a system that holds still the car when facing a climb;

3. *aeb* is a security system that performs automatic emergency brakes at relatively low speeds when an obstacle such another vehicle or a pedestrian occupies the roadway;

4. *acc* is one of the most complex systems which performs adaptive speed control, maintaining the desired speed, but adjusting it with respect to the safety distance from other vehicles.

The second category, on the other hand, groups the infotainment systems. These variables have also been coded as dummy in the following way:

$$IN_m = \begin{cases} 1, & \text{if } IN_m \text{ is included} \\ 0, & \text{if } IN_m \text{ is not included} \end{cases} \tag{3.5}$$

The total of infotainment systems is m=10. Also in this case we can recognize three clusters of variables, grouped in relation to the type of service that is provided to the customer. The first is linked to the increased connectivity of new car models with the driver's personal devices:

1. *usb* is one of the most common interfaces that allows to connect mobile devices to the car;

2. *touch_pad* is a relatively new feature in cars and allows to have a smoother experience while controlling onboard tasks;
3. *smart_key* indicates the possibility of using a virtual car key via the smartphone;
4. *smart_int* is a variable that describes the presence of ad-hoc smartphone interfaces embedded in the automobile's software;
5. *home* indicates domotic services accessible from the car.

The second contains three other variables that describe digital services obtained thanks to the use of integrated sensors:

1. *vcom* represents the possibility of accessing to infotainment and performing different tasks using vocal commands and gestures;
2. *gest* indicates the presence of sensors to open automatically the vehicle's trunk;
3. *ele_key* is the electronic key which is detected from the car and opens the door when is close.

Finally, the last two variables considered in the first model describe those systems that increase the amount of information obtainable by the driver while driving:

1. *virtual* is the virtual cockpit, an advanced information reporting system; the driver is able to customize the information according to his needs;
2. *hud* is the head-up display which projects useful information into the driver's field of vision without the driver having to take his eyes off the road.

As for the second model, however, the explanatory variables are two empirical indices, respectively $Automation_{score}$ and $DigitSer_{score}$. The latter were calculated from the variables that have just been described for the first model. The aim is to obtain aggregate indices that describes the quantity of ADAS systems and the overall level of automation obtained in each vehicle and the offer of infotainment and digital services.

The first index, $Automation_{score}$, was calculated taking into account the level of automation (see table 1.1) obtainable by embedding each system belonging to the category of AD variables in the car. No system independently allows to reach level 2 of automation. However, the combination of some of these, such as *ldws* and *acc*, is able to perform both longitudinal and lateral control of the vehicle, meeting the requirements for level 2 automation. Therefore, an additional variable has been created to describe this kind of combinations. In light of this, the formula used to calculate $Automation_{score,\ c}$ for car c is:

$$Automation_{score,c} = \alpha Score_{0,c} + \beta Score_{1,c} + \gamma Score_{2,c} \quad (3.6)$$

Where $Score_{i,\ c}$ is a score calculated with respect to the systems belonging to the *i-th* level of automation embedded in car c. These terms are obtained as follows:

$$Score_{i,c} = 10 \cdot \frac{Sum_{i,c} - Min(Sum_i)}{Max(Sum_i) - Min(Sum_i)} \quad (3.7)$$

Where $Sum_{i,\ c}$ is the sum of variables related to systems of the *i-th* level of automation embedded in car c, while $Min(Sum_i)$ and $Max(Sum_i)$ are respectively the minimum and the maximum value of the sum of attributes of level i among all vehicles.

As for parameters α, β and γ, they have been estimated using three different functions. The system of equation describing the conditions to be met is the following:

$$\begin{cases} \alpha = f(0) \\ \beta = f(1) \\ \gamma = f(2) \\ \alpha + \beta + \gamma = 1 \end{cases} \tag{3.8}$$

The first functional form used to estimate the parameters is linear, the second is logarithmic and the third one is exponential:

$$\begin{cases} f(x) = mx + q \\ f(x) = qe^{mx} \\ f(x) = ln(mx+1) + q \end{cases} \tag{3.9}$$

In order to solve the systems, in all the cases, the parameter q has been set to 0,15. In table 3.2 there is an overview of the values obtained solving the equation system 3.8 for each parameter with the different functional forms described in equation 3.9.

Functional form	$\boldsymbol{m}$	α	β	γ
Linear	0,018	0,15	0,33	0,52
Exponential	0,066	0,15	0,29	0,56
Logarithmic	0,021	0,15	0,34	0,51

Table 3.2: Parameter estimates to weight $Score_{i,c}$

A similar methodology has been used to estimate index $DigitSer_{score,\ c}$ for each car c. In fact:

$$DigitSer_{score,c} = \alpha Score_{1,c} + \beta Score_{2,c} + \gamma Score_{3,c} \quad (3.10)$$

Where $Score_{j,c}$ is the score obtained by each car c relatively to infotainment systems belonging to the *j-th* cluster described above in this chapter ("connectivity", "sensors" and "information"). Each score is calculated as follows:

$$Score_{j,c} = 10 \cdot \frac{Sum_{j,c} - Min(Sum_j)}{Max(Sum_j) - Min(Sum_j)} \quad (3.11)$$

Also in this case, $Sum_{j,\ c}$ is the sum of variables related to systems of the *j-th* cluster, embedded in car c.$Min(Sum_j)$ and $Max(Sum_i)$ report the minimum and the maximum value of the sum of attributes of cluster j among all vehicles. In this case weight parameters have all been set to the same value as there is not a clear relationship between the three clusters:

$$\alpha = \beta = \gamma = \frac{1}{3} \quad (3.12)$$

Both $Automation_{score}$ and $DigitSer_{score}$ are continuous variables with values included in the interval [0,10]. In chapter 4 statistics about all the variables here described will be given.

3.4.3 Control variables

The control variables used in both models describe two aspects of each car in the database, as seen in equations (3.2) and (3.3):

1. M_p are $p = 8$ variables that qualitatively describe characteristics of the different

models;

2. V_q are $q = 5$ are control variables that refer to features that take on different values for each version.

Among the *Mp* variables, three describe the market of origin of the brand to which the model belongs. They are coded as dummy, the value assigned is 1 if the brand originates from a nation included in the corresponding geographical area:

1. *emea* for cars coming from the Europe, Middle East and Africa area;

2. *nafta* for cars coming from the United States, Canada and Mexico;

3. *apac* for cars coming from the Asia and Pacific area.

Another variable linked to the brand and codified as dummy is *luxury*. This indicates whether the brand to which the model belongs is considered to be premium. The *diff_launch* variable indicates the number of years since the launch of model on the Italian market and assumes integer numerical values. Finally, three other variables *maxi_suv*, *suv* and *crossover* indicate that the model belongs to one of the corresponding categories.

The V_q variables, as anticipated, describe the single version of the car. *cm3_tho*, *hp_hund* and *length_mt* indicate for each car the displacement in thousands of cubic centimeters, the engine horsepower in hundreds and the length in meters. The values assumed by these three variables are positive real numbers. The *electric* variable, coded as dummy, takes on a value of 1 if the car has a full electric motor; the choice to include this variable in the model is dictated by the fact that for this type f vehicle there is no displacement value, with a consequent distortion of the analysis results. Finally, the *hifi* variable was included as it is an option with a high price for the consumer, however often integrated in the higher-end versions.

Chapter 4

Analysis and Results

Chapter 4 reports the results of the analyses carried out to verify the two hypotheses set out at the beginning of Chapter 3. First, the descriptive statistics of the database regarding the variables involved are presented, followed by the process of identification of the outliers. Finally, the results regarding the two models are shown separately together with the robustness checks and comments on the regression coefficients obtained.

4.1 Descriptive Statistics

The presentation of the descriptive statistics of the dataset follows the order in which the variables were presented in chapter 3.

As anticipated before, the dependent variable *ln_price* has a distribution closer to normal than the price (fig.3.1). The mean, variances and skewness and kurtosis are shown in table 4.1.

The frequencies of the explanatory variables of the first model related to ADAS

Var. name	Min.	Max.	Mean	Variance	Skew.	Kurt.
ln_price	9,52	12,39	10,75	0,24	0,62	3,15

Table 4.1: Variable *ln_price summary*

have been grouped in the table 4.2 in descending order with respect to the frequency with which they occur over the total of the observations present in the database. The systems with the highest frequency are parking sensor, which have long been present on vehicles and automatic emergency braking, which is increasingly considered indispensable as a safety device. The complex park assist system is the least present on the vehicles examined.

Variable name	0	1	Percentage %
sensors	406	1149	73,89%
aeb	424	1131	72,73%
camera	550	1005	64,63%
hhc	596	959	61,67%
lka	654	901	57,94%
tsr	720	835	53,70%
dcm	740	815	52,41%
acc	915	640	41,16%
ahb	926	629	40,45%
bsm	1011	544	34,98%
ldws	1118	437	28,10%
hdc	1237	318	20,45%
pa	1345	210	13,50%

Table 4.2: ADAS-related variables frequencies

A similar table has been drawn up for the frequencies of the infotainment-related variables. Also in this case, since we are dealing with variables coded as dummy (assuming therefore the values 0 or 1), in fact, it was possible to summarize them in a single table. In this case, some systems such as the touch pad and the smart key are poorly represented in the dataset. The hud system, on the other hand, has a relatively high presence, with a frequency of 20,39%.

Variable name	**0**	**1**	**Percentage %**
usb	110	1445	92,93%
ele_key	620	935	60,13%
gest	1174	381	24,50%
hud	1238	317	20,39%
smart_int	1353	202	12,99%
vcom	1376	179	11,51%
home	1413	142	9,13%
virtual	1425	130	8,36%
touch_pad	1517	38	2,44%
smart_key	1523	32	2,06%

Table 4.3: Infotainment-related variables frequencies

The explanatory variables of the second model, $Automation_{score}$ and $DigitSer_{score}$ are summarize in the table 4.4, reporting the values of the various measures approximated to the two decimal digits. For the $Automation_{score}$, three different values are presented and reflect the distributions obtained using the three different parameter sets calculated as indicated in chapter 3. The quotes *li*, *ex* and *ln* indicate the different models used to obtain the parameters.

Var. name	**Min.**	**Max.**	**Mean**	**Variance**	**Skew.**	**Kurt.**
$\mathrm{Automation_{score}}^{li}$	0,00	9,25	3,76	8,11	0,72	1,83
$\mathrm{Automation_{score}}^{ex}$	0,00	9,44	3,61	9,89	0,78	1,79
$\mathrm{Automation_{score}}^{ln}$	0,00	9,44	3,65	9,00	0,76	1,81
$\mathrm{DigitSer_{score}}$	0,00	10,00	2,88	3,42	1,15	3,85

Table 4.4: $Automation_{score}$ and $DigitSer_{score}$ *summary*

The frequencies relative to the country of origin of the models examined, shown in table 4.5, shows a clear majority as regards the cars produced by European OEMs.

The variable that describes the "age" of the model is shown in table 4.6. The

Variable name	Number of models	Percentage %
emea	1191	76,59%
apac	288	18,52%
nafta	76	4,89%

Table 4.5: Frequency for car's country of origin

minimum value assumed by the variable is two years, while the average value is about five years. This data, however, does not take into account the updates made to the models, which in any case affect the equipment of the cars.

Var. name	Min.	Max.	Mean	Variance	Skew.	Kurt.
diff_launch	2	16	5,03	3,90	0,29	2,79

Table 4.6: Variable *diff_launch* summary

Table 4.7, on the other hand, shows information about the distribution of the database with respect to the three categories taken into consideration. SUVs and crossovers are represented in substantially equal measure. The cars belonging to the maxi-suv category represent about five percent of the total sample. The table also shows the number of vehicles belonging to brands considered to be luxury

Information regarding the *cm3_tho*, *hp_hund* and *length_mt* variables are shown in table 4.8. The variable *cm3_tho* has a minimum value of zero linked to the presence of full electric cars that, as mentioned above, do not have a displacement value.

Lastly, the variable that describes the presence of a hi-fi system takes on a value of 1 in 31.38% of cases.

Variable name	Number of models	Percentage %
suv	733	47,14%
crossover	700	45,02%
maxi_suv	76	4,89%
luxury	151	9,71%

Table 4.7: Frequency of car's segment and luxury models

Var. name	Min.	Max.	Mean	Variance	Skew.	Kurt.
cm3_tho	0,00	5,00	1,77	0,69	0,45	4,41
hp_hund	0,45	6,80	2,09	1,16	1,61	5,59
length_mt	3,73	5,21	4,51	0,07	0,65	2,82

Table 4.8: Version-related variables summary

4.2 Outliers identification

As OLS is affected by outliers, before performing the analysis an outliers identification process has been performed. To do so, a box plot has been graphed (fig. 4.1) for the *price* variable in order to eliminate more variability from the sample. The graph has been plotted using and inter-quartile range of 1,5 points.

All cars with a retail price higher than 109121 € result to be outliers and thus 83 observations have been dropped from the database.

4.3 Results and comments - First Model

This section shows the results obtained from the analysis carried out on the dataset, deprived of outliers, using the first model. The statistical software Stata was used to carry out the analyses. The presentation of the results is followed by statistical tests to verify that the hypotheses of the hedonic price model are respected and, finally, by comments on the results obtained.

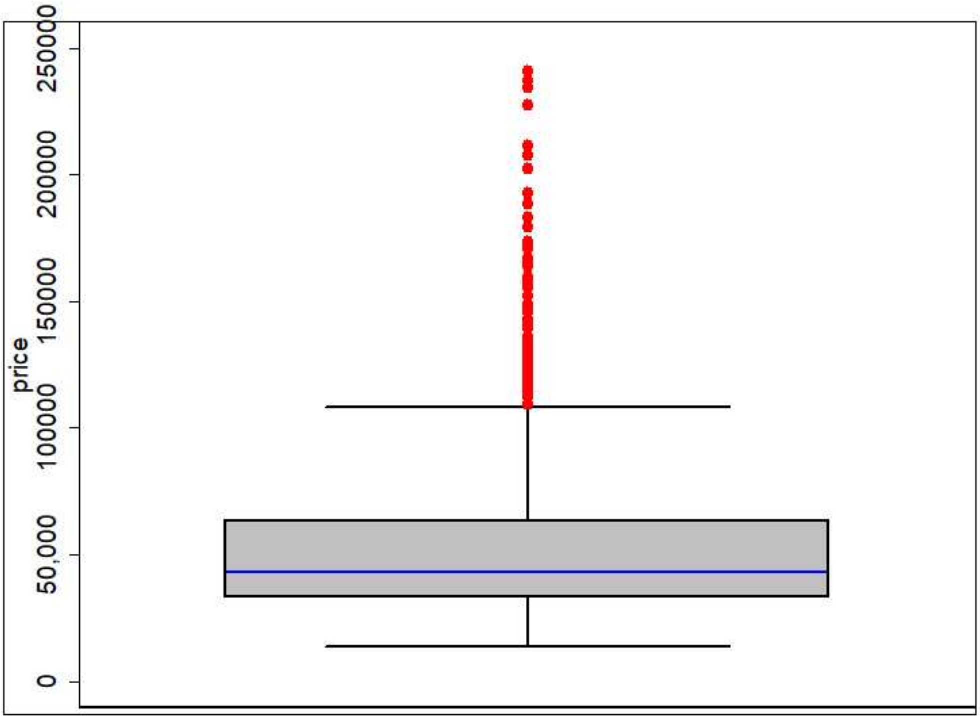

Figure 4.1: Boxplot showing outliers in variable *price* distribution.

4.3.1 Results

Figure 4.2 shows the results of the first analysis. The *emea* and *crossover* variables have been omitted as they are mutually exclusive to *nafta* and *apac* and *maxi_suv* and *suv* respectively. In this way, the collinearity between these two groups of variables is avoided and the results are to be read taking as a reference a crossover belonging to an European brand. The value of the r^2 obtained is 0.8904 and the *adjusted*-r^2 is 0.8878. The F-test which evaluates the null hypothesis that all regression coefficients are equal to zero versus the alternative that at least one is not no is rejected and therefore the relationship between dependent and independent variables is statistically reliable.

With regard to the explanatory variables, both for those regarding ADAS and infotainment systems, the *p-values* obtained do not allow in all cases to reject the H_0 hypothesis that there is no statistically significant relationship between the dependent variable and the independent variables examined. For *AD* variables, the following are included among those not statistically significant:

- *sensors*;
- *pa*;
- *tsr*;
- *ldws*;
- *lka*.

As far as *ldws* and *pa* are concerned, referring to table 4.2, these were among the least represented systems in the sample, unlike the other three variables, which assumed non-zero value in at least 53,70% of cases.

For the variables of the *IN* group there are four cases in which the *p-value* exceeds the threshold value of 0.05:

- *smart_key*;
- *vcom*;
- *ele_key*;
- *virtual*;

In this case, three of the variables were present in less than 11,51% of the models examined (see table 4.3), while the electronic key was the second most represented add-on with 60,13% of cars equipped with this system.

Lastly, also among control variables statistic significance is not achieved by two variables, respectively *nafta* and *diff_launch*, with *p-values* equal to 0,958 and 0,259.

ln_price	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
camera	.0374215	.0106527	3.51	0.000	.0165249	.0583181
sensors	-.0145705	.0105453	-1.38	0.167	-.0352563	.0061153
pa	.0082721	.014494	0.57	0.568	-.0201595	.0367037
ahb	.0376651	.0098342	3.83	0.000	.0183741	.0569561
tsr	.013003	.0092929	1.40	0.162	-.005226	.0312321
bsm	.0382722	.0094067	4.07	0.000	.0198199	.0567245
dcm	-.0304946	.010241	-2.98	0.003	-.0505835	-.0104057
ldws	-.0046495	.0133911	-0.35	0.728	-.0309177	.0216187
lka	-.007479	.0137954	-0.54	0.588	-.0345402	.0195823
hdc	.0367342	.0117642	3.12	0.002	.0136573	.059811
hhc	-.0371615	.0118682	-3.13	0.002	-.0604423	-.0138807
aeb	.0629568	.0116442	5.41	0.000	.0401153	.0857983
acc	.0435184	.0096023	4.53	0.000	.0246824	.0623544
usb	.0507883	.0186043	2.73	0.006	.0142939	.0872828
touch_pad	.3459773	.0323107	10.71	0.000	.282596	.4093585
smart_key	.0159785	.0327877	0.49	0.626	-.0483383	.0802954
smart_int	.0382002	.0146605	2.61	0.009	.0094418	.0669586
home	-.0537547	.0203451	-2.64	0.008	-.0936639	-.0138455
vcom	.0127114	.0207082	0.61	0.539	-.0279102	.053333
gest	.0565181	.0115631	4.89	0.000	.0338357	.0792005
ele_key	-.0072345	.0099851	-0.72	0.469	-.0268214	.0123525
virtual	-.0239506	.0178113	-1.34	0.179	-.0588895	.0109883
hud	.0335784	.0134107	2.50	0.012	.0072718	.059885
nafta	-.0010113	.0192385	-0.05	0.958	-.0387499	.0367273
apac	-.1323757	.011674	-11.34	0.000	-.1552755	-.1094758
luxury	.1503826	.0200684	7.49	0.000	.1110162	.189749
diff_launch	-.002628	.0023284	-1.13	0.259	-.0071954	.0019393
maxi_suv	-.1618074	.0244392	-6.62	0.000	-.2097478	-.1138671
suv	-.0622109	.0123108	-5.05	0.000	-.08636	-.0380618
cm3_tho	.1266972	.0109162	11.61	0.000	.1052837	.1481107
electric	.3616064	.0237637	15.22	0.000	.314991	.4082217
hp_hund	.1898067	.0070645	26.87	0.000	.1759489	.2036646
length_mt	.6247898	.034151	18.29	0.000	.5577986	.691781
hifi	.0581943	.0116055	5.01	0.000	.0354288	.0809598
_cons	7.175339	.1484437	48.34	0.000	6.88415	7.466529

Figure 4.2: Hypothesis 1 regression results

4.3.2 Robustness check

Before moving on to the comments of the analysis, a robustness check was carried out to verify that the assumptions relating to the adopted model were respected. In particular, the following were checked:

1. Non-multicollinearity of independent variables;
2. Normal distribution of residuals;
3. Homoscedasticity of residuals.

The correlation between the independent variables is shown in figure 4.3. As mentioned above the *emea* and *crossover* variables were omitted from the regression due to the perfect collinearity with respect to other variables due to the exclusive nature of the attributes they represent. The 34 variables, including explanatory and control ones, used in the model are subject to the multicollinearity test presented. The values obtained are generally acceptable and do not indicate critical relationships between the variables involved. However, as an index of possible multicollinearity, the coefficients obtained in correspondence with the following pairs of variables should be noted:

- *length_mt-hp_hund*: 0,70 which indicates a quite strong positive relationship between the two variables;
- *luxury-vcom*: 0,64 which indicates a quite strong positive relationship between the two variables;
- *lka-ldws*: -0,64 which represents a quite strong negative relationship between the two variables;

- *length_mt-hhc*: -0,59 which indicates a quite strong negative relationship between the two variables;
- *length_mt-cm3_tho*: 0,58 which indicates a quite strong positive relationship between the two variables;
- *hp_hund-hhc*: -0,54 which indicates a quite strong negative relationship between the two variables.

The relationship between the *electric* and *cm3_tho* variables was deliberately ignored downstream of the considerations made in the section 4.3.3 of the previous chapter. Furthermore, the variance inflation factor (VIF) was calculated to detect the severity of multicollinearity in the regression analysis. The highest values detected are, respectively, 4,80 and 4,61 corresponding to *length_mt* and *cm3_tho*. These values are, however, far from the threshold value of 10. Therefore, it is possible to consider the first hypothesis of non-multicollinearity of the independent variables verified.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1-camera	1,00																
2-sensors	0,41	1,00															
3-pa	0,21	0,11	1,00														
4-ahb	0,12	0,00	0,18	1,00													
5-tsr	0,06	0,03	-0,06	0,07	1,00												
6-bsm	0,22	0,15	0,20	0,30	0,21	1,00											
7-dcm	0,37	0,36	-0,01	0,02	0,14	0,14	1,00										
8-ldws	-0,16	-0,06	0,03	-0,23	0,10	-0,05	-0,04	1,00									
9-lka	0,44	0,28	0,08	0,16	0,06	0,10	0,24	-0,64	1,00								
10-hdc	0,14	0,08	0,16	0,13	-0,07	-0,04	-0,05	0,05	0,08	1,00							
11-hhc	-0,15	-0,01	-0,31	-0,15	0,23	0,11	-0,03	-0,03	0,04	-0,10	1,00						
12-aeb	0,35	0,38	0,09	0,01	0,10	0,14	0,37	0,00	0,41	0,09	-0,07	1,00					
13-acc	0,23	0,14	0,11	0,23	0,01	0,28	0,23	-0,14	0,24	0,17	0,07	0,23	1,00				
14-usb	-0,07	0,04	-0,24	-0,04	0,04	0,00	0,25	0,00	-0,15	-0,11	0,33	-0,11	0,13	1,00			
15-touch_pad	0,12	0,09	-0,06	0,18	-0,18	-0,01	0,15	-0,10	0,14	0,34	0,12	0,10	0,20	0,04	1,00		
16-smart_key	0,10	0,02	0,18	0,16	0,01	0,02	-0,09	0,03	0,01	0,08	-0,18	0,01	-0,11	-0,07	-0,02	1,00	
17-smart_int	-0,15	-0,17	0,33	-0,02	-0,01	-0,06	-0,35	0,23	-0,13	0,13	-0,10	-0,13	-0,09	-0,27	-0,06	0,27	1,00
18-home	0,21	0,06	0,30	0,12	0,07	-0,07	0,08	0,02	0,13	0,24	-0,26	0,11	0,05	-0,20	0,32	0,04	0,10
19-vcom	0,21	0,10	0,17	0,06	0,13	0,09	0,25	0,04	-0,02	-0,09	-0,06	0,07	-0,10	0,07	-0,05	0,03	-0,03
20-gest	0,27	0,22	0,17	0,22	0,11	0,23	0,18	-0,02	0,16	0,11	-0,21	0,17	0,12	-0,14	0,22	0,12	-0,09
21-ele_key	0,47	0,27	0,16	0,16	0,10	0,21	0,33	-0,04	0,31	0,07	-0,17	0,39	0,27	-0,06	0,07	0,08	-0,12
22-virtual	0,06	0,09	0,37	0,18	-0,14	0,06	0,00	0,03	-0,06	0,13	-0,07	0,10	0,06	-0,02	-0,05	0,33	0,28
23-hud	0,19	0,04	0,27	0,23	0,24	0,20	0,12	0,00	0,02	-0,04	-0,10	0,03	0,12	-0,11	-0,08	0,06	0,03
24-nafta	-0,01	0,08	-0,08	-0,08	-0,08	-0,14	-0,20	0,00	0,04	-0,04	0,13	0,09	0,07	0,06	-0,04	-0,03	0,09
25-apac	0,22	0,10	-0,15	0,08	0,16	0,15	0,16	-0,13	0,23	0,07	0,14	-0,02	0,28	0,07	-0,08	-0,06	-0,19
26-luxury	0,18	0,12	-0,05	-0,03	0,19	0,01	0,20	0,08	0,00	-0,05	-0,14	0,06	-0,20	0,04	-0,05	-0,04	-0,11
27-diff_launch	-0,11	-0,06	0,07	-0,14	-0,05	-0,09	-0,12	0,26	-0,13	0,06	0,06	-0,15	0,01	-0,09	-0,01	-0,08	0,35
28-maxi_suv	-0,04	0,02	-0,02	0,05	-0,05	-0,05	0,09	0,10	-0,02	-0,01	-0,31	0,14	-0,07	-0,17	-0,04	0,19	-0,04
29-suv	0,30	0,17	0,27	0,30	-0,13	0,05	0,09	0,02	0,13	0,36	-0,15	0,19	0,23	-0,11	0,17	0,04	0,11
30-cm3_tho	0,17	-0,08	0,22	0,24	-0,07	0,01	0,02	0,07	-0,04	0,19	-0,31	0,11	0,09	-0,23	0,04	0,06	0,13
31-electric	0,05	0,08	0,02	-0,03	0,05	-0,01	0,01	-0,10	0,12	-0,12	-0,10	-0,02	-0,02	-0,03	-0,04	0,09	-0,05
32-hp_hund	0,28	0,02	0,33	0,23	-0,02	0,00	0,06	0,00	0,03	0,20	-0,54	0,12	0,07	-0,29	0,07	0,15	0,11
33-length_mt	0,30	0,04	0,35	0,22	0,01	0,05	0,14	0,13	0,00	0,18	-0,59	0,18	0,09	-0,37	-0,08	0,17	0,04
34-hifi	0,10	-0,02	0,31	0,28	0,06	0,05	0,04	0,12	-0,05	0,07	-0,15	0,06	0,00	-0,11	0,14	0,14	0,25

	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34
18-home	1,00																
19-vcom	0,20	1,00															
20-gest	0,37	0,24	1,00														
21-ele_key	0,24	0,14	0,40	1,00													
22-virtual	-0,05	0,20	0,05	0,11	1,00												
23-hud	0,40	0,43	0,28	0,28	0,11	1,00											
24-nafta	-0,07	-0,07	-0,01	0,02	-0,07	-0,11	1,00										
25-apac	-0,14	-0,15	0,01	0,12	-0,15	0,02	-0,12	1,00									
26-luxury	0,21	0,64	0,17	0,07	-0,09	0,20	-0,05	-0,15	1,00								
27-diff_launch	0,00	0,05	-0,04	-0,11	0,14	-0,05	0,09	-0,17	-0,01	1,00							
28-maxi_suv	-0,01	-0,03	0,23	0,04	0,10	0,04	-0,02	0,00	-0,07	-0,02	1,00						
29-suv	0,25	0,27	0,25	0,15	0,16	0,09	0,18	-0,10	0,27	-0,01	-0,21	1,00					
30-cm3_tho	0,26	0,12	0,13	0,10	0,17	0,24	-0,02	-0,08	0,13	0,14	0,18	0,39	1,00				
31-electric	-0,04	0,03	0,05	0,07	-0,06	-0,01	-0,04	0,04	0,01	-0,25	-0,06	-0,09	-0,63	1,00			
32-hp_hund	0,32	0,22	0,27	0,21	0,14	0,22	-0,02	-0,15	0,27	-0,04	0,17	0,38	0,50	0,05	1,00		
33-length_mt	0,32	0,14	0,33	0,27	0,10	0,23	-0,05	-0,04	0,17	-0,08	0,40	0,41	0,58	-0,06	0,70	1,00	
34-hifi	0,45	0,36	0,24	0,26	0,32	0,46	-0,09	-0,30	0,19	0,16	0,04	0,18	0,22	-0,09	0,23	0,17	1,00

Figure 4.3: Hypothesis 1 multicollinearity check

Two graphical methods and two statistical methods were used to test the second hypothesis. The first graph (in figure 4.4) is a P-P plot (probability-probability plot) which relates the two cumulative probability distributions belonging respectively to the residuals and the normal. The scatterplot obtained is not perfectly aligned with the line in the center of the graph, indicating that the distribution of the residuals does not exactly fit the normal.

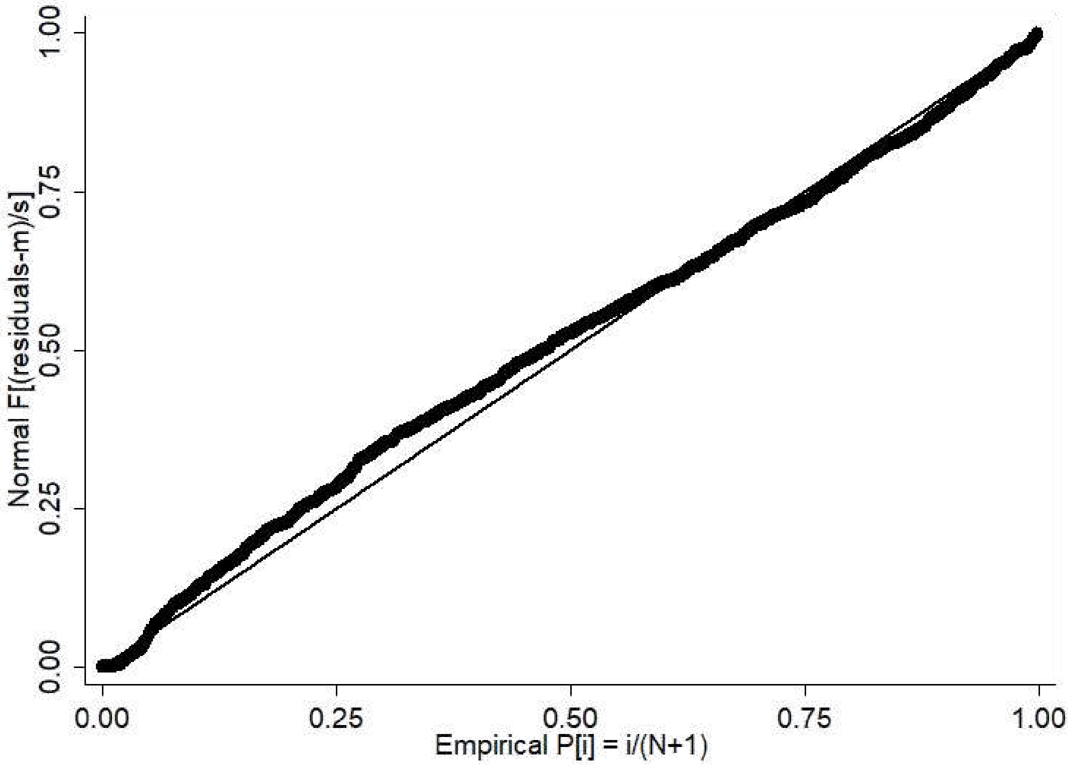

Figure 4.4: P-P plot for first model's regression residuals

The second graph (figure 4.5) is instead a Q-Q plot (quantile-quantile plot) that compares the quantiles corresponding to the distribution of residuals with those of the normal. In this case, at the extremes the scatterplot does not align on the central line.

The statistical tests performed are the Jarque-Brera test and the Shapiro-Wilk test. In both cases the null hypothesis have to be rejected and thus the distribution of residuals doesn't appear to be normally distributed.

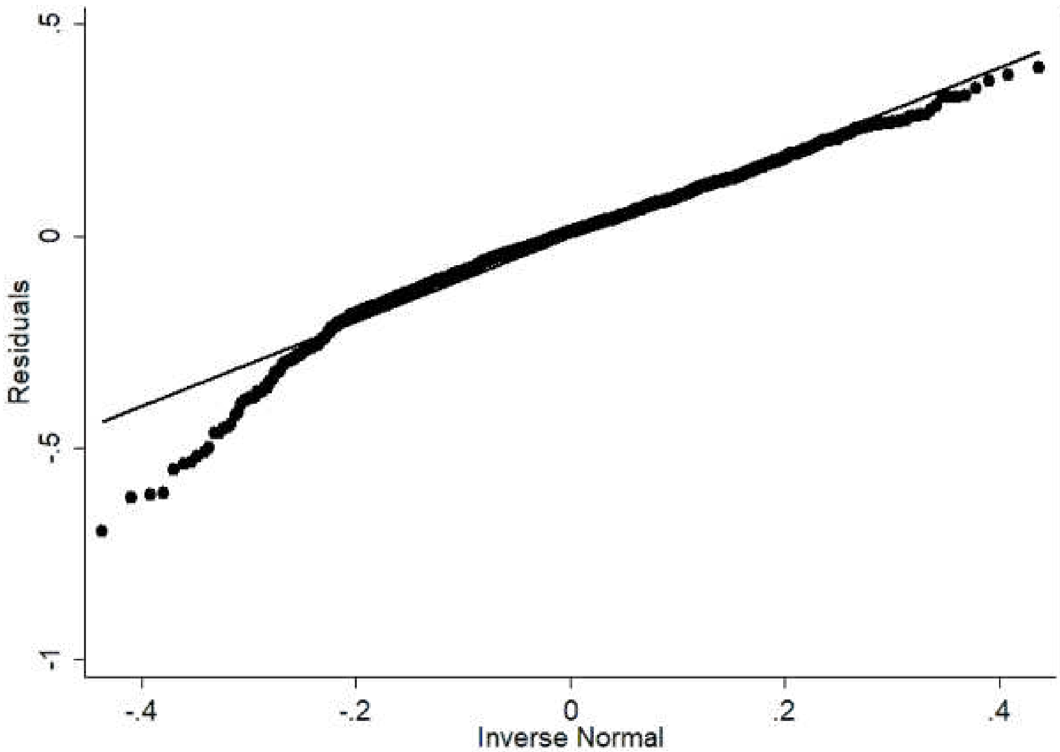

Figure 4.5: Q-Q plot for first model's regression residuals

Also the Breusch-Pagan heteroskedasticity test the null hypothesis has to be rejected determining the non homoskedasticity of residuals.

4.3.3 Comments

The independent variables of the first model are characterized, for the most part, by a dummy encoding. This situation determines the need to make a consideration before moving on to commenting the results. In fact, the percentage effect of dummy variables, as stated in Chapter 2 is not equal to the regression coefficient related to the variable but can be calculated as.

$$\frac{\delta y_i}{y} = (e^{\beta_i} - 1) \qquad (4.1)$$

Downstream of this observation, it is possible to comment the regression coefficients obtained during the first analysis and reported in Figure 4.2. As for the control variables, the first two to consider are those that refer to the Country of origin of the vehicle. The coefficients obtained for the *nafta* and *apac* variables are -0,001 and -0,132 respectively. However, remembering that both were coded as dummies, and therefore using Equation 4.1, we obtain two new values that describe the real percentage change in price when the corresponding characteristics occur. They are:

- *nafta* = -0,001;
- *apac* = -0,124.

Compared to a car from an OEM based in Europe, with the same other characteristics, the price for a car belonging to a North American brand remains substantially unchanged, while it decreases by 12,4% in the case of an Asian vehicles. For cars belonging to luxury brands, the coefficient is equal to 16,2%.

The coefficient relating to the *diff_launch* variable is equal to -0,002, indicating a decrease of 0,2 percentage points in the price for each year that has passed since the launch on the market of the model under consideration. This substantially negligible value is justifiable considering that there is not a great difference in "age" of the models considered, The *maxi_su*v and *suv* variables are coded as dummies; therefore, the coefficients to be considered are:

- *maxi_suv* = -0,149;
- *suv* = -0,060.

In this case, other characteristics being equal, vehicles belonging to the maxi-suv or suv category have prices 14.9% and 6.0% lower than a crossover.

Turning instead to the V_q variables corresponding to the different versions, the new coefficient for the *electric* variable (which takes a value of 1 if the car has a fully electric motor) is equal to 0,436. This indicates a 43,6% increase in value compared to other types of engines. However, it should be noted that this effect is balanced by that of the *cm3_tho* variable which for electric cars always assumes a value of 0. For every thousand cubic centimeters of displacement, in fact, the percentage increase in price is equal to 12,7%. Furthermore, the percentage increase for every hundred horsepower and for every meter of vehicle length is 19,0% and 62,5%. These coefficients are consistent with expectations, both as regards the signs and the absolute values assumed. Finally the *hifi* variable also determines an increase in the value of the car equal to 6,0%.

For the thirteen variables labeled as *AD* and coded as dummy, table 4.9 shows the percentage effects on the final price of the car in descending order of value.

From the table it is possible to see how the systems that have the most positive impact on the value of the car are those ADAS devices designed to increase safety while driving, such as blind spot monitoring (*bsm*), advanced cruce control (*acc*) and the automatic emergency brake (*aeb*). The presence of the latter determines an increase of 6,5 percent points compared to the price of the car, all other variables

Variable name	Dummy coefficient	Real percentage effect
aeb	0,063	6,5%
acc	0,044	4,4%
bsm	0,038	3,9%
ahb	0,038	3,8%
camera	0,037	3,8%
hdc	0,037	3,7%
tsr	0,013	1,3%
pa	0,008	0,8%
ldws	-0,005	-0,5%
lka	-0,007	-0,7%
sensors	-0,015	-1,4%
dcm	-0,030	-3,0%
hhc	-0,037	-3,6%

Table 4.9: *AD* variables percentage effects on price.

being equal. The effects are still positive as regards the automatic high beams (*ahb*, +3.8%), rear cameras to control the surroundings during parking maneuvers (*camera*, +3.8%) and the hill descent control (*hdc* , +3.7%). The effect of the presence of parking sensors (*sensors*, -1.4%) is instead slightly negative. This may be due to the fact that this type of system is considered obsolete compared to rear cameras or the more modern park assist (*pa*, +0.8%) and tends to be less present in premium models.

Some options, such as the Traffic Sign Recognition (*tsr*, +1.3%), the Lane Departure Warning System (*ldws*, -0.5%) and the Lane Keeping Assist (*lka*, -0.7%) have the minor effects on the final price, in absolute value.

On the other hand, the effects on the price detected by the presence of the *dcm* and *hhc* variables are clearly negative.

Table 4.10 refers to the ten variables corresponding to the optionals of the infotainment category, labeled as *IN*; ordered with the same principle as Table 4.9.

Variable name	Dummy coefficient	Real percentage effect
touch_pad	0,346	41,3%
gest	0,057	5,8%
usb	0,051	5,2%
smart_int	0,038	3,9%
hud	0,034	3,4%
smart_key	0,016	1,6%
vcom	0,013	1,3%
ele_key	-0,007	-0,7%
virtual	-0,024	-2,4%
home	-0,054	-5,2%

Table 4.10: *IN* variables percentage effects on price.

The value obtained in correspondence with the *touch_pad* variable is surprising, equal to 41,3%. This can be justified considering that the touch interface is nowadays the most widespread on the electronics market, starting with smartphones. The possibility of having a device equipped with this feature in the car could be a real source of added value for the consumer, accustomed to this type of interaction, also due to the greater perceived comfort compared to the use of classic interfaces.

The values obtained are generally consistent with expectations, having positive coefficients in almost all cases. The effect of the voice commands and the electronic key is lower compared to other systems. The impact of virtual cockpits and car-accessible home automation services is slightly negative, probably linked to the presence of the aforementioned services in a too small sample of models examined.

4.4 Results and comments - Second Model

The second model presents as explanatory variables two empirical indices calculated starting from the information present in the dataset. The first index, $automation_{score}$ was calculated, as indicated in chapter 3, estimating three parameters. In this section, the results of the analysis related to the second hypothesis object of this study are reported, emphasizing the results of the regression whose $automation_{score}$ was calculated assuming:

$$\alpha = 0{,}15; \quad \beta = 0{,}33; \quad \gamma = 0{,}52 \quad (4.2)$$

4.4.1 Results

Just as in the case of the first model, here too the *emea* and *crossover* variables have been omitted for the reasons listed above. The decision to use the parameters given in the equation (4.2) is essentially linked to reason of higher consistency in the model. However, the results of the regressions, regardless of the parameters used to estimate the $automation_{score}$, are consistent with each other. In fact, the signs associated with all the regression coefficients are in agreement, as well as the indications obtainable from the *p-values* recorded. As for the values of r^2 and *adjusted-*r^2 they are in all three cases higher than 0,86. For the regression shown in figure 4.6, in particular, an r^2 equal to 0,8653 and an *adjusted-*r^2 of 0,8641 are recorded. The small difference between the two values, which can be noticed substantially to the third decimal place, indicates a good quality of the variables included in the model. In all three cases, the variable *nafta* is not statistically relevant, probably due to the poor representation of models from American OEMs in the sample (see table 4.5. The *suv* variable, on the other hand, has a significance level of 90%. For the other variables, the level stands at 99%. Also in this case, the null hypothesis of the F-test is rejected.

ln_price	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
automation_score	.0143436	.0016267	8.82	0.000	.0111526	.0175346
digitser_score	.0212588	.0031519	6.74	0.000	.0150761	.0274414
nafta	-.0154743	.0189451	-0.82	0.414	-.0526368	.0216882
apac	-.1407699	.0115753	-12.16	0.000	-.1634758	-.1180639
luxury	.1135132	.0157021	7.23	0.000	.0827121	.1443144
diff_launch	-.0068691	.0021653	-3.17	0.002	-.0111165	-.0026217
maxi_suv	-.104764	.0231362	-4.53	0.000	-.1501478	-.0593801
suv	-.0198505	.0109435	-1.81	0.070	-.0413173	.0016162
cm3_tho	.1325563	.0112987	11.73	0.000	.1103928	.1547197
electric	.3611095	.0250362	14.42	0.000	.3119987	.4102202
hp_hund	.2113517	.0073682	28.68	0.000	.1968983	.2258051
length_mt	.5458143	.0309851	17.62	0.000	.4850342	.6065943
hifi	.0610817	.0117711	5.19	0.000	.0379916	.0841717
_cons	7.514186	.1266012	59.35	0.000	7.265846	7.762526

Figure 4.6: Hypothesis 2 regression results

4.4.2 Robustness check

The figure 4.7 shows the collinearity coefficients obtained by comparing the 13 independent variables used in the regression. There are no worrying values, however it is worth noting, in descending order of absolute value, the relationships between the following pairs of variables:

- *length_mt-hp_hund*: 0,70 which indicates a quite strong positive relationship between the two variables;
- *hifi-DigitSer*$_{score}$: 0,60 which indicates a quite strong positive relationship between the two variables;
- *length_mt-cm3_tho*: 0,58 which indicates a quite strong positive relationship between the two variables.

The VIF values, in this case, are even farther from the threshold value of 10 with respect to ones registered in section 4.3.2. In particular, the maximum values obtained are, respectively, 4,08 for *cm3_tho*, 3,26 for *length_mt* and 2,66 for *electric*.

This result is in accordance with the values observable in the table shown in figure 4.7; however, multicollinearity of independent variables is rejected.

	1	2	3	4	5	6	7	8	9	10	11	12	13
1-automation_score	1,00												
2-digitser_score	0,20	1,00											
3-nafta	-0,02	-0,06	1,00										
4-apac	0,34	-0,09	-0,12	1,00									
5-luxury	-0,12	0,24	-0,05	-0,15	1,00								
6-diff_launch	-0,05	0,04	0,09	-0,17	-0,01	1,00							
7-maxi_suv	-0,06	0,08	-0,02	0,00	-0,07	-0,02	1,00						
8-suv	0,25	0,30	0,18	-0,10	0,27	-0,01	-0,21	1,00					
9-cm3_tho	0,07	0,26	-0,02	-0,08	0,13	0,14	0,18	0,39	1,00				
10-electric	-0,03	0,00	-0,04	0,04	0,01	-0,25	-0,06	-0,09	-0,63	1,00			
11-hp_hund	0,07	0,35	-0,02	-0,15	0,27	-0,04	0,17	0,38	0,50	0,05	1,00		
12-length_mt	0,09	0,32	-0,05	-0,04	0,17	-0,08	0,40	0,41	0,58	-0,06	0,70	1,00	
13-hifi	-0,02	0,60	-0,09	-0,30	0,19	0,16	0,04	0,18	0,22	-0,09	0,23	0,17	1,00

Figure 4.7: Hypothesis 2 multicollinearity check

To verify that the residuals have a normal distribution, two graphs were plotted, a P-P plot and a Q-Q plot. From the first (figure 4.8) it is clear that the points obtained rest almost completely on the central line. This indicates that the cumulative probability distribution of the residuals and the normal are substantially identical.

The scatterplot obtained by comparing the quartiles of the residuals distribution and the normal distribution, on the other hand, shows differences for the values in the tails of the two distributions. In the central section of the graph, however, there is an excellent correspondence of the points with respect to the central line.

The graphs obtained are quite satisfactory, especially for the P-P plots, even for the regressions performed using the different $Automation_{score}$ values. However, in all cases, the hypothesis of the tests of Jarque-Brera and Shapiro-Wilk normality tests are to be rejected. In any case, a further graph (figure 4.10) is presented. It

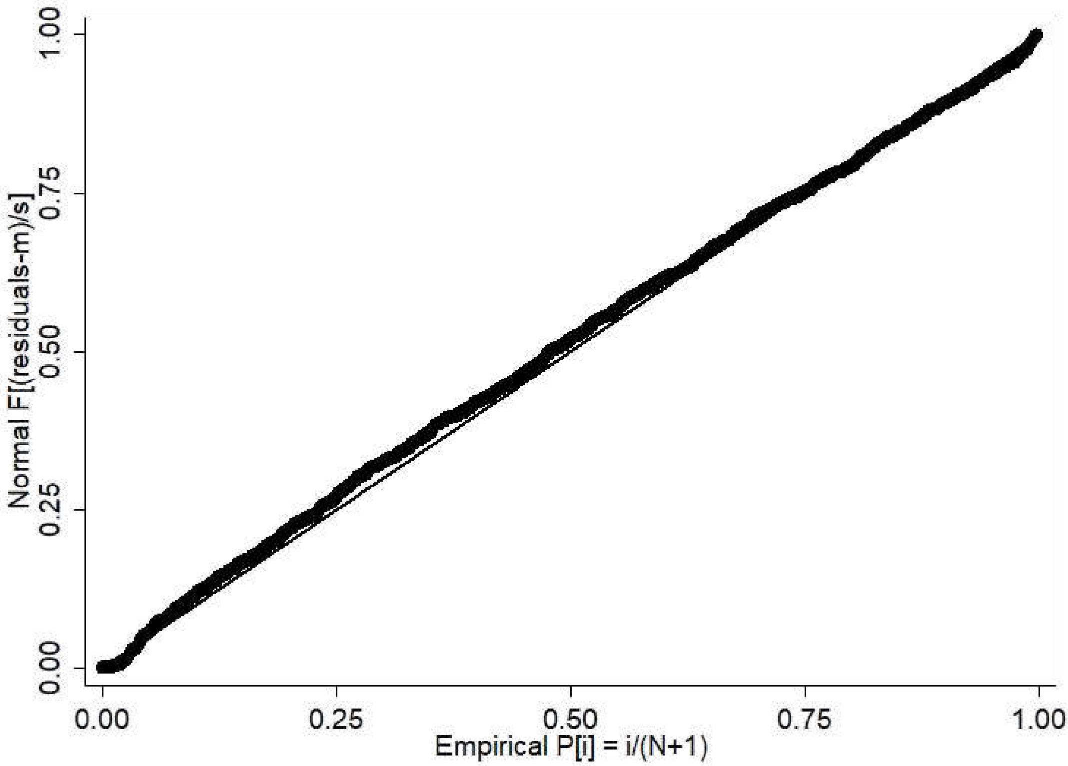

Figure 4.8: P-P plot for second model's regression residuals

represents the kernel density plot of the residuals (an estimation of their distribution) in relation to the normal. The two curves appear to be overlapping for the most part.

As for homoskedasticity, the Breusch-Pagan test performed on the sample has a negative result, therefore the null hypothesis has to be rejected as in the first case.

4.4.3 Comments

Considering the analysis results reported in Figure 4.6, the coefficients obtained for the control variables during the second analysis are consistent with those obtained during the first analysis, in terms of sign and absolute value.

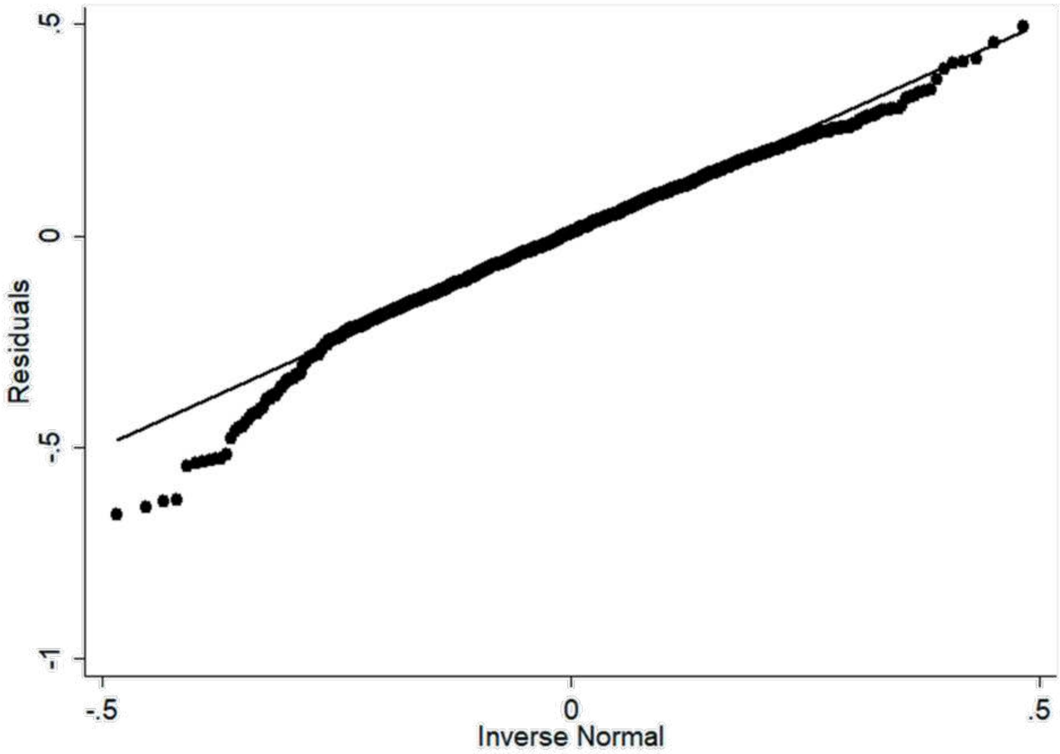

Figure 4.9: Q-Q plot for second model's regression residuals

The coefficients adjusted according to the Equation 4.1 are shown in Table 4.11. The considerations relating to the variables *nafta* and *apac*, as well as those relating to the variables *luxury* and *diff_launch* are similar to those made in the previous case. Slightly less significant, in absolute value, is the effect related to the type of car. The relationship between the *electric* and *cm3_tho* variables is essentially the same. The effect on the price remains constant and positive for every hundred horsepower (*hp*, +21.1%), for every meter of car length (*length_mt*, +54.6 %) and for the presence of a hi-fi system (*hifi*, +6.1 %).

The effects recorded for the two explanatory variables are consistent with expectations.

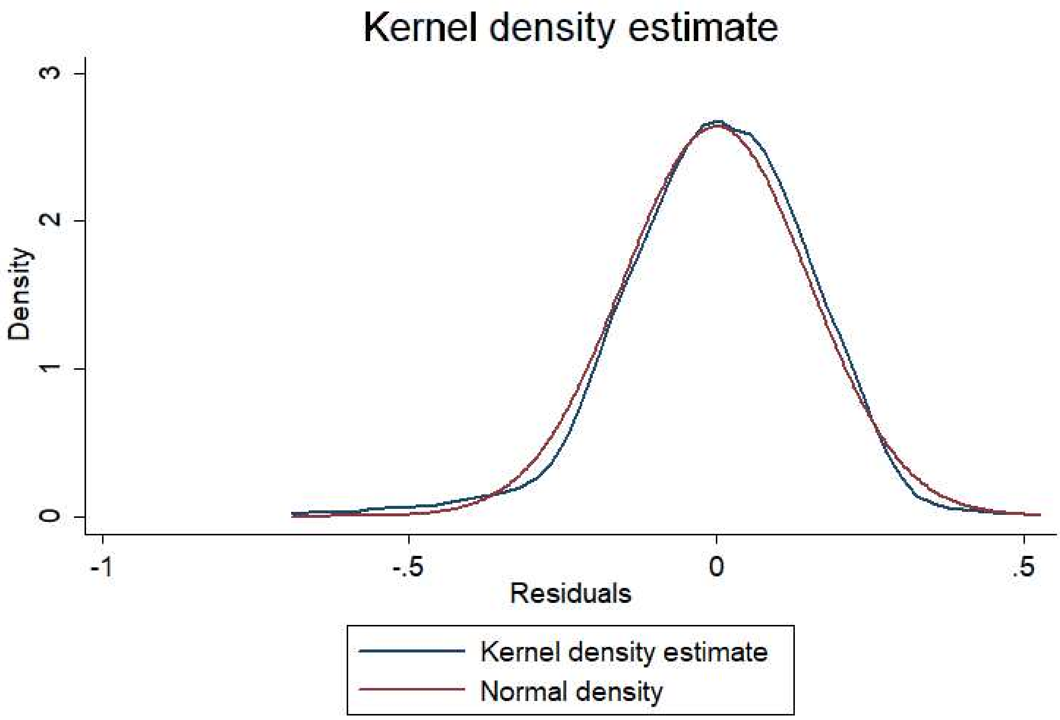

Figure 4.10: Residuals density plot vs normal

Variable name	Dummy coefficient	Real percentage effect
nafta	-0,015	-1,5%
apac	-0,141	-13,1%
luxury	0,114	12,0%
maxi_suv	-0,105	-9,9%
suv	-0,020	-2,0%
electric	0,361	43,5%
hifi	0,061	6,3%

Table 4.11: Second regression dummy control variables percentage effects on price.

The β_1 regression coefficient relating to the $Automation_{score}$ assumes a value of 0,014. Recalling that the maximum value that can be assumed by the variable is equal to 10, as indicated in Chapter 3, the maximum percentage effect on car value from the presence of ADAS systems is 14,3%.

Similarly, the β_2 regression coefficient relating to the infotainment systems is equal to 0,021. In correspondence with the maximum value of the $DigitSer_{score}$ variable, the percentage increase in the value of the car is equal to 21,3%.

Chapter 5

Conclusions and Suggestions for Future Studies

The last chapter reports considerations regarding the study carried out, in relation to the two research hypotheses presented in the chapter 3 and subjected to the analysis presented in the chapter 4 carried out using the hedonic prices model. Subsequently, the results obtained in the two cases are then compared. Finally, the limits of this work are presented and ideas for future research are suggested.

5.1 Hypothesis validation

The results obtained in Chapter 4 can now be explicitly related to the hypotheses made in Chapter 3. The first hypothesis presented is:

"The presence of each system integrated in the car in order to make it a smart connected product is positively correlated with its value."

Considering the coefficients obtained downstream of the regression analysis, it is not possible to accept this hypothesis and, therefore, it has to be rejected. In fact, there are some variables for which the relative regressor assumes negative values, even if often with minimal negative effects on the total value of the car. On the other hand, various systems emerge whose presence increase, even considerably, the value of the vehicle in the eyes of the customer.

However, it may be of interest to analyze the relationship between the diffusion of the various systems on the models represented in the sample and the relative percentage effects on the final price of the car. Figure 5.1 shows the percentage presence and the real effect on the price for each system considered, with the exception of *touch_pad*. The choice to exclude this variable from the graph is dictated exclusively by reasons of scale and readability of the graph itself, given the large difference between the value of the regressor assumed by this variable compared with the others.

Observing the graph it is possible to notice four different zones (which we will indicate with cardinal coordinates), that we will describe clockwise, starting from the upper right quadrant:

1. NW: features present on more than 50% of the cars examined and with positive effects on value;

2. SW: very common features which, however, have a negative effect on the price;

3. SE: not very common systems that appear to have regressors with negative sign downstream of the analysis;

4. NE: features present on few models that have a positive effect on the final price of the car (including the touch pad, *touch_pad*).

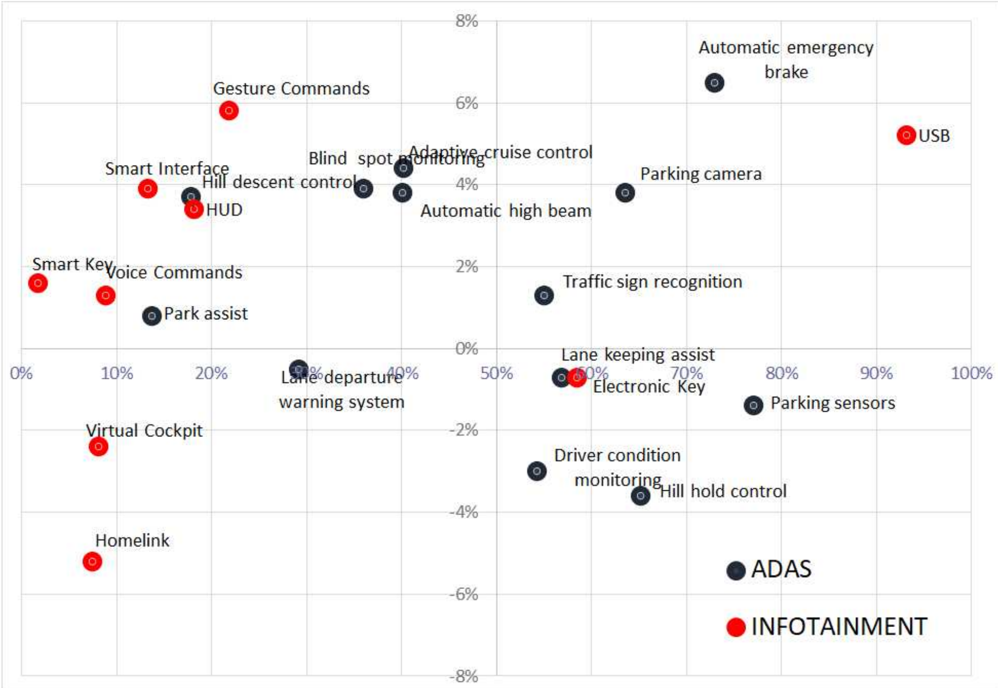

Figure 5.1: Diffusion of ADAS and infotainment systems vs their effect on car prices.

The graph shown in Figure 5.1 allows us to better analyze the current state of the adoption of digital technologies within the automotive industry. Furthermore, using three frameworks, which will be briefly described below, it is possible to speculate on the future opportunities for automotive industry's stakeholders, in particular, OEMs and suppliers. Each system will therefore be analyzed though three main dimensions:

1. The possibility of satisfying consumer needs, measured by using the willingness to pay as a proxy of the utility obtained from the presence of each add-on obtained through the analysis of Hedonic Prices;
2. The current state of adoption of the technology, measured via the diffusion of each system with respect to the sample making up the dataset;

3. The possibility of generating business with large margins and market share for stakeholders in the near future.

The Kano model relates the needs of consumers with the attributes possessed by a product. It defines several ways in which the latter affect customer satisfaction in relation to their implementation in the product itself:

- Must-be attributes: their presence does not give satisfaction to the consumer, as they are considered to be mandatory. If a product lacks this kind of attributes the effect will be a critical dissatisfaction of the client;
- Attractive attributes: they are functions that do not cause disutility to the consumer if not implemented; if present, on the other hand, they generate a lot of satisfaction;
- One-dimensional attributes: some attributes are considered essential, the failure to implement such attributes causes the non-satisfaction of needs for consumers, while their presence causes a positive effect;
- Indifferent attributes: they respond to non-explicit customer needs, their implementation could have a positive effect on overall satisfaction;
- Reverse attributes: unlike the other attributes, their presence generates dissatisfaction in the customer.

Now we recall the theory of Abernathy and Utterback for products characterized by multiple components. Even if it is true that the car is not a "new" product, it is possible to imagine the smart components of the car as a disruptive modification of the automobile paradigm itself. In this context, it is possible to identify different states of adoption of the technologies implemented nowadays in a car. Downstream of this consideration, based on the percentage presence of each one of the systems analyzed in the dataset, we distinguish technologies facing different phases:

- Fluid phase: a phase characterized by an immature technology which could have relatively low performances and face a lower demand;
- Transition phase: the emergence of a dominant architecture determines the features that the product should have;
- Specific phase: demand for these technologies grows exponentially, determining the need to optimize production processes in order to exploit economic revenues.

Finally, we can use the information obtained so far to speculate on the possible growth opportunity relating to the implementation of the various components and give indication for suppliers of the aforementioned subsystems and OEMs about the possibility of investing in order to obtain an advantageous position with respect to the competitor. In doing this, we will refer to the terminology of the Boston Consulting Group's Growth-Share matrix used for the management of a company's business portfolio. In particular, we will refer to:

- Stars: businesses which have high market shares and high growth opportunities, as well as high cash flows;
- Cash cows: businesses which have high market shares and low growth opportunities, but medium cash flows;
- Dogs: activities that should be divested as they have both low market shares and growth opportunities, as well as near-to-zero or negative cash flows;

- Question marks: businesses which have high growth opportunities but limited market share, with a more uncertain outcome.

The first three systems that we will analyze are the automatic emergency brake, the parking cameras and the USB connectivity (described respectively by the variables *aeb*, *camera* and *usb*. The results of the analysis of the Hedonic Prices returned positive (and greater than the 2%) regressors for these three components, indicating that their presence has a positive value in the eyes of consumers. Also due to their high diffusion within the dataset (more than 50%) it is possible to conclude that these attributes belong to the driver's performance needs. The integration of these technologies into the product also appears to be at a mature stage. For these reasons, the growth opportunities for suppliers of these systems appear to be limited, and the margin obtainable by OEMs towards the consumers appear moderate. For the automatic emergency brake, it should also be noted that legislation could make the implementation of this system mandatory -just like seatbelts- thus making it a must-be attribute, generating opportunities for the developers of such systems who will be able to obtain significant market shares among their competitors.

Now we will analyze traffic sign recognition, lane keeping assist, electronic key and parking sensors. The regression carried out has reported coefficients included in the interval [-2%, +2%] for these systems. These four attributes were also present in more than 50% of the cars examined. In this case the percentage effect on price related to the presence of such attributes is close to zero. This leads us to classify them as indifferent attributes. From another point of view, they may have undergone a commoditization process, for example in the case of parking sensors, which have long been integrated into cars and are considered essentially as must-be.

Again, the growth opportunities for suppliers of such systems appear limited, as do the opportunities for product differentiation by OEMs. On the other hand, excluding such systems could lead to a dissatisfaction of the final consumer.

Considering the results obtained for driver condition monitoring and hill hold control, two systems belonging to the *ADAS* category, their presence determines a percentage decrease in prices with a value higher than 3%, the lowest among these systems. Furthermore, their presence on the vehicles examined is relatively high. This result is surprising as it would be logical to conclude that the presence of these attributes generates a dissatisfaction in the consumer. Therefore, we postpone the analysis of these systems to studies specifically calibrated to investigate this phenomenon.

Moving on to the portion comprised between 30% and 50% of representation in the dataset of the graph in Figure 5.1, we find three technologies in a transition phase towards the diffusion on most cars. These are adaptive cruise control, automatic high beam and blind spot monitoring, referred to as *acc*, *ahb* and *bsm*. For these three systems the percentage effect on the price (already reported in Table 4.9) is respectively 4,4%, 3,8% and 3,9%. As these are driver assistance systems, future regulation could make the implementation of these technologies mandatory, just like the case of the automatic emergency brake. To date, it seems reasonable to think that they satisfy performance needs instead. In light of this and of the technology adoption phase, the opportunities for growth and value generation for the consumer are placed in an intermediate position with respect to the variables located in other areas of the aforementioned graph.

Continuing to move along the different areas of the chart, in the SE sector we find systems with a negative effect and a representation in the sample of less than 30%.

The virtual cockpit and home automation control are located in this area, described by the variables *virtual_cockpit* and *home*. The negative effect obtained from the regression places these two optionals in the category of reverse attributes according to Kano's model. In fact, consumers may still be reluctant to adopt such solutions, in a still relatively fluid phase of development. The business opportunities linked to these attributes are question marks since, although the growth opportunities appear to be high, the reactions of a wider audience of consumers are still uncertain.

The situation is similar for the optionals described by the *smart_key*, *pa* and *ldws* variables. Also in this case, in fact, the marginal effects close to zero in absolute value set them as systems with interesting future developments.

The HUD, on the other hand, with a real effect of 3.4% and relative low diffusion, can already be placed within the one-directional attributes with good growth prospects.

Finally, we find some optionals with diffusion currently below the 30% of the total versions and positive percentage effects in relation to the price of the car. In this latest cluster we find the gesture control, the smart interfaces, the hill descent control and the touch pads. It is clear that, as for now, these attributes belong to the category of attractive attributes. For the suppliers of these systems, the possibility of obtaining preponderant market shares lays the foundations for businesses that can be categorized as stars. The growth potential appears very high, as is the value for consumers. At a strategic level, the development of the core competencies necessary for their implementation could prove decisive in tackling the transition towards the world of digital cars. The resources generated in this way could be exploited to support the development of other similar technologies, perhaps belonging to the most promising of those described above.

Let us now consider the second hypothesis formulated:

"The value of a car is positively correlated with the presence of features and optionals that increase the degree of automation and that increase connectivity and the possibility to use digital services"

Following the definition of the two scores, also presented in Chapter 3, it clearly emerges that the greater presence of ADAS and Infotainment systems in one vehicle compared to another significantly increases its value, reaching a maximum price increase of respectively 14,3% and 21.3%. The second hypothesis can therefore be considered accepted.

By further analyzing the dataset, we calculated the average values assumed by the two *scores* in relation to the market of origin of the producer brand. The $automation_{score}$ was calculated using the parameters reported in equation (4.2). Table 5.1 shows, for each market to which it belongs, the average of the two scores and the average effect on price calculated taking into account the regressors obtained in Chapter 4.

Market	**Avg. Automation$_{\mathbf{score}}$**	**Avg. DigitSer$_{\mathbf{score}}$**
emea	3,21	2,85
nafta	3,47	2,31
apac	5,63	2,44

Table 5.1: Average values of $automation_{score}$ and $digitser_{score}$ with respect to the OEM market of origin.

It is possible to notice how the value of the $automation_{score}$ is on average much higher for the cars coming from Asian markets. On the other hand, the difference regarding the $digitser_{score}$ is smaller and in favor of European carmakers.

Carrying out an even more detailed analysis, the averages for both scores were calculated with respect to the individual brands taken into consideration. Figure

5.2 shows the results obtained for the 29 brands represented by at least ten versions within the dataset.

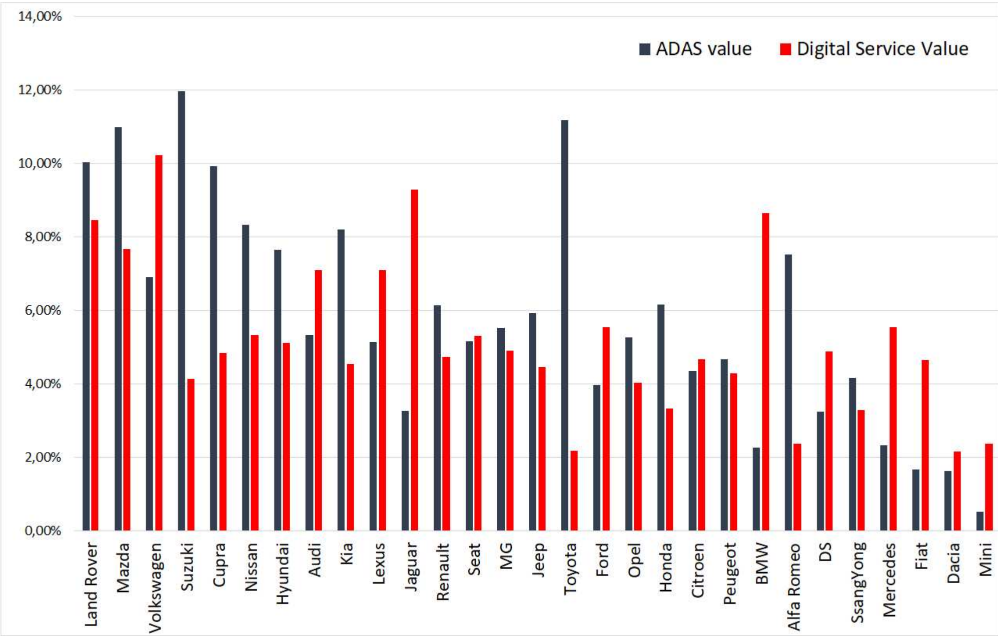

Figure 5.2: Average $automation_{score}$ and $digitser_{score}$ for each brand

The brands that have the highest average scores in the *ADAS* category are Suzuki, Toyota and Mazda, de facto verifying the information obtained by observing the data shown in table 5.1. The best three brands in the *infotainment* category are Volkswagen, Jaguar and BMW, once again, in line with what was previously observed. Before making further considerations, it should be noted that the presence of North American brands within the dataset is certainly limited compared to that of Asian and, above all, European brands. It still appears clear how the focus of the OEMs belonging to different geographic areas is set on either one of the two different aspects taken into consideration.

5.2 Limits and further Research goals

With a view to conducting further studies on the subject, some limitations and ideas relating to this work are presented below. In the first instance, it could be interesting to explore other more complex mathematical models on which to base the hedonic, for example exploiting the indications presented during the analysis of Chapter 2.

As regards the dataset, however, the possibility of collecting information relating to a less limited time frame could reveal interesting changes related to the evolution of the phenomenon in relation to the impact of the various systems and subsystems considered. Furthermore, conducting similar studies focusing on different segments of the automotive market, such as that of subcompact cars, could dare a broader and more complete vision of the phenomenon. Similarly, the analysis of national markets that are different or wider than the Italian one could reveal useful information for all stakeholders interested in the phenomenon as a whole.

Moreover, starting from the evidence presented in Chapter 4, there are various research ideas in investigating in greater depth the causes that justify the results obtained in correspondence of the considered variables.

Finally, as regards the second model, the mainly quantitative nature of the two designed parameters could hide some effects and implications deriving from the difference in the systems made available by the various OEMs in terms of quality and reliability. To overcome this, the attempt to give different weights to the less technologically advanced features has been made, especially by calculating the $automation_{score}$. However it could be of some interest to investigate the presence of this kind of effects by focusing an analysis on a subset of the features -or even a single one- investigated in this work.

5.3 Final comments

The digital revolution in the automotive industry is underway; the expected changes related to the way of doing business of the actors involved, as well as the habits of consumers will be multiple and, in some cases, radical. In this work a qualitative analysis of the current situation concerning this phenomenon was carried out, with a focus on the structure of the industry and on the opportunities (and dangers) that all stakeholders will be able to exploit (or should avoid). A quantitative analysis was then presented, proposing models that could validate the effect of these transformations, in our opinion successfully.

Bibliography

[1] Nils Urbach, Frederik Ahlemann, Tilo Böhmann, Paul Drews, Walter Brenner, Florian Schaudel, and Reinhard Schütte. «The impact of digitalization on the IT department». In: *Business & information systems engineering* 61.1 (2019), pp. 123–131 (cit. on p. 2).

[2] Henning Kagermann, Wolf-Dieter Lukas, and Wolfgang Wahlster. «Industrie 4.0: Mit dem Internet der Dinge auf dem Weg zur 4. industriellen Revolution». In: *VDI nachrichten* 13.1 (2011), pp. 2–3 (cit. on p. 2).

[3] René Riedl, Alexander Benlian, Thomas Hess, Dirk Stelzer, and Hermann Sikora. «On the relationship between information management and digitalization». In: *Business & Information Systems Engineering* 59.6 (2017), pp. 475–482 (cit. on pp. 2, 10).

[4] Kerstin Felser and Martin G Wynn. «Digitalization and Evolving IT Sourcing Strategies in the German Automotive Industry». In: *International Journal on Advances in Intelligent Systems* 13.3/4 (2020), pp. 212–225 (cit. on pp. 2, 24, 25).

[5] Gregory Vial. «Understanding digital transformation: A review and a research agenda». In: *Managing Digital Transformation* (2021), pp. 13–66 (cit. on p. 2).

[6] Christof Ebert and Carlos Henrique C Duarte. «Digital transformation.» In: *IEEE Softw.* 35.4 (2018), pp. 16–21 (cit. on p. 3).

[7] Agnieszka Radziwon, Arne Bilberg, Marcel Bogers, and Erik Skov Madsen. «The smart factory: exploring adaptive and flexible manufacturing solutions». In: *Procedia engineering* 69 (2014), pp. 1184–1190 (cit. on p. 3).

[8] Andre Hanelt, Everlin Piccinini, Robert W Gregory, Björn Hildebrandt, and Lutz M Kolbe. «Digital Transformation of Primarily Physical Industries-Exploring the Impact of Digital Trends on Business Models of Automobile Manufacturers.» In: *Wirtschaftsinformatik* 88.3-5 (2015), pp. 1313–1327 (cit. on pp. 3, 5, 9).

[9] Michael E Porter and James E Heppelmann. «How smart, connected products are transforming competition». In: *Harvard business review* 92.11 (2014), pp. 64–88 (cit. on pp. 3, 8).

[10] Michael Porter, Eric Snow, and Kathleen Mitford. «Strategic Choices in Building the Smart Connected Mine». In: *Harvard Business Review* (2014) (cit. on p. 4).

[11] Giovanni Gavetti, Rebecca Henderson, and Simona Giorgi. *Kodak and the digital revolution (A)*. Harvard Business School Publishing, 2005 (cit. on p. 5).

[12] Marisa Saglietto. «L'evoluzione della mobilità e la trasformazione dell'industria automotive». In: *Osservatorio sulla componentistica automotive italiana 2018* (2018), pp. 75–85 (cit. on pp. 5, 6).

[13] Carlos Llopis-Albert, Francisco Rubio, and Francisco Valero. «Impact of digital transformation on the automotive industry». In: *Technological forecasting and social change* 162 (2021), p. 120343 (cit. on p. 6).

[14] Andrew L Riker, Henry Ford, Thomas Edison, Glenn Martin, Orville Wright, and Charles Kettering. «SAE International». In: (2005) (cit. on p. 7).

[15] Lisa Marie Zankel, Paul Gerber, Verena Zimmermann, and Nina Gerber. «Taking on driving tasks yourself? That was yesterday! How drivers would like to be supported by assistance systems». In: *13th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*. 2021, pp. 71–76 (cit. on p. 7).

[16] Inc. Cisco Systems. *Che cos'è il 5G?* `https://www.cisco.com/c/it_it/solutions/what-is-5g.html`. [Online; accessed 08-September-2022]. 2022 (cit. on pp. 10, 11).

[17] Infodata. *Cosa è il 5G e perché tutti vogliono il nuovo "web"? Spiegato bene.* `https://www.infodata.ilsole24ore.com/2019/08/18/cosa-5g-perche-tutti-vogliono-web-spiegato-bene/`. [Online; accessed 08-September-2022]. 2022 (cit. on pp. 10, 11).

[18] Kevin Ashton et al. «That 'internet of things' thing». In: *RFID journal* 22.7 (2009), pp. 97–114 (cit. on p. 11).

[19] Keyur K Patel, Sunil M Patel, and P Scholar. «Internet of things-IOT: definition, characteristics, architecture, enabling technologies, application & future challenges». In: *International journal of engineering science and computing* 6.5 (2016) (cit. on p. 11).

[20] Luigi Atzori, Antonio Iera, and Giacomo Morabito. «The internet of things: A survey». In: *Computer networks* 54.15 (2010), pp. 2787–2805 (cit. on p. 12).

[21] Peter Mell, Tim Grance, et al. «The NIST definition of cloud computing». In: (2011) (cit. on pp. 12, 13).

[22] Qi Zhang, Lu Cheng, and Raouf Boutaba. «Cloud computing: state-of-the-art and research challenges». In: *Journal of internet services and applications* 1.1 (2010), pp. 7–18 (cit. on p. 13).

[23] Ralph H Rasshofer, Martin Spies, and Hans Spies. «Influences of weather phenomena on automotive laser radar systems». In: *Advances in Radio Science* 9.B. 2 (2011), pp. 49–60 (cit. on pp. 14, 15).

[24] Martin Schneider. «Automotive radar-status and trends». In: *German microwave conference*. 2005, pp. 144–147 (cit. on p. 15).

[25] Abdallah Moujahid, Mounir ElAraki Tantaoui, Manolo Dulva Hina, Assia Soukane, Andrea Ortalda, Ahmed ElKhadimi, and Amar Ramdane-Cherif. «Machine learning techniques in ADAS: a review». In: *2018 International Conference on Advances in Computing and Communication Engineering (ICACCE)*. IEEE. 2018, pp. 235–242 (cit. on pp. 16, 17).

[26] Yi Hou, Praveen Edara, and Carlos Sun. «Modeling mandatory lane changing using Bayes classifier and decision trees». In: *IEEE Transactions on Intelligent Transportation Systems* 15.2 (2013), pp. 647–655 (cit. on p. 17).

[27] Robert M Grant. *Contemporary strategy analysis*. John Wiley & Sons, 2021 (cit. on p. 18).

[28] Tobias Riasanow, Gabriela Galic, and Markus Böhm. «Digital transformation in the automotive industry: towards a generic value network». In: (2017) (cit. on p. 19).

[29] Simon Chanias and Thomas Hess. «Understanding Digital Transformation Strategy formation: Insights from Europe's Automotive Industry.» In: *PACIS 2016* (2016), p. 296 (cit. on p. 24).

[30] Daniel Alvarez-Coello, Daniel Wilms, Adnan Bekan, and Jorge Marx Gómez. «Towards a data-centric architecture in the automotive industry». In: *Procedia Computer Science* 181 (2021), pp. 658–663 (cit. on p. 25).

[31] Alberto Carmone. *Addio Daimler AG, nasce Mercedes-Benz Group AG.* `https://it.motor1.com/news/564546/daimler-ag-diventa-mercedes-group/`. [Online; accessed 12-June-2022]. 2022 (cit. on p. 25).

[32] Nicodemo Angì Marco Scotti. *Tutto sul piano industriale da 60 miliardi di Mercedes. Parla il ceo Italia.* `https://www.industriaitaliana.it/mercedes-piano-industriale-auto-elettrica/`. [Online; accessed 12-June-2022]. 2022 (cit. on pp. 25, 26).

[33] EconomyUp. *Pagamenti in-car, nel 2022 il primo sistema per comprare e pagare direttamente con l'auto.* `https://www.economyup.it/automotive/connected-car/pagamenti-in-car-nel-2022-il-primo-sistema-per-comprare-e-pagare-direttamente-con-lauto/`. [Online; accessed 12-June-2022]. 2022 (cit. on p. 26).

[34] Alessandro Lago. *La smart #1 dice no grazie a Apple CarPlay e Android Auto.* `https://insideevs.it/news/578861/smart-no-apple-carplay-android/`. [Online; accessed 12-June-2022]. 2022 (cit. on p. 26).

[35] Angelo Maria Perrino. *L'app Free Now parla romano, Javarone: "Il traffico si vince con la tecnologia.* https://www.affaritaliani.it/roma/l-app-free-now-parla-romano-javarone-il-traffico-si-vince-con-la-tecnologia-797915.html?refresh_ce. [Online; accessed 12-June-2022]. 2022 (cit. on p. 26).

[36] Stellantis. *Grazie alla diversità che ci alimenta, guidiamo il modo in cui il mondo si muove.* https://www.stellantis.com/it/il-gruppo/chi-siamo. [Online; accessed 13-June-2022]. 2022 (cit. on p. 27).

[37] Stellantis. *Dare Forward 2030.* https://www.stellantis.com/it/investors/eventi/strategic-plan. [Online; accessed 13-June-2022]. 2022 (cit. on p. 27).

[38] Nicodemo Angì. *Stellantis: un altro tassello della strategia digitale.* https://www.alvolante.it/news/stellantis-accordo-qualcomm-strategia-digitale-377789. [Online; accessed 13-June-2022]. 2022 (cit. on p. 27).

[39] Filippo Einaudi. *Stellantis si allea con Amazon per creare auto sempre più hi-tech.* https://it.motor1.com/news/558876/stellantis-amazon-accordo-smartcockpit/. [Online; accessed 13-June-2022]. 2022 (cit. on p. 27).

[40] Giacomo Dotta. *Alfa Romeo Tonale: compri su Amazon, ricevi nel bagagliaio.* https://www.punto-informatico.it/alfa-romeo-tonale-amazon-bagagliaio/. [Online; accessed 13-June-2022]. 2022 (cit. on p. 28).

[41] Vincenzo Borgomeo. *L'idea dell'Alfa Romeo Tonale: la certificazione dell'usato arriva con un Nft.* https://www.repubblica.it/tecnologia/2022/02/18/

news/idea_alfa_romeo_tonale_la_certificazione_dellusato_arriva_da_un_nft-337733079/. [Online; accessed 13-June-2022]. 2022 (cit. on p. 28).

[42] Lisa Gordon. *Palantir Announces Global Enterprise Deal with Stellantis.* https://www.businesswire.com/news/home/20220524006162/en/Palantir-Announces-Global-Enterprise-Deal-with-Stellantis. [Online; accessed 13-June-2022]. 2022 (cit. on p. 28).

[43] Massimiliano Carrà. *Stellantis acquisisce Share Now: obiettivo 2,8 miliardi di euro di ricavi nel car sharing.* https://forbes.it/2022/05/03/stellantis-acquisisce-share-now-obiettivo-28-miliardi-di-euro-di-ricavi-nel-car-sharing/. [Online; accessed 13-June-2022]. 2022 (cit. on p. 28).

[44] Domenico Aliperto. *Stellantis si dà al venture capital: sul piatto 300 milioni per le startup dell'automotive.* https://www.corrierecomunicazioni.it/digital-economy/stellantis-si-da-al-venture-capital-sul-piatto-300-milioni-per-le-startup-dellautomotive/. [Online; accessed 13-June-2022]. 2022 (cit. on p. 28).

[45] Alberto Annicchiarico. *New Auto, la nuova strategia Volkswagen per il 2030.* https://www.ilsole24ore.com/art/volkswagen-cambia-carte-vertici-gruppo-diess-software-e-strategia-AELLVu1. [Online; accessed 16-June-2022]. 2021 (cit. on p. 29).

[46] Savina Confaloni. *New Auto, la nuova strategia Volkswagen per il 2030.* https://www.corriere.it/motori/anteprime/21_luglio_14/new-auto-nuova-strategia-volkswagen-il-2030-f1e2c528-e475-11eb-9ca3-9397dc78a855.shtml?refresh_ce. [Online; accessed 16-June-2022]. 2021 (cit. on p. 29).

[47] IlSole24Ore. *Gruppo Volkswagen, tre nuove partnership per lo sviluppo e la produzione di batterie*. https://www.ilsole24ore.com/art/gruppo-volkswagen-tre-nuove-partnership-lo-sviluppo-e-produzione-batterie-AELUbL7. [Online; accessed 16-June-2022]. 2022 (cit. on p. 29).

[48] Volkswagen Group News. *Volkswagen starts mobility services on Astypalea, marking next step in Greek island's electrification*. https://www.volkswagen-newsroom.com/en/press-releases/volkswagen-starts-mobility-services-on-astypalea-marking-next-step-in-greek-islands-electrification-7994. [Online; accessed 16-June-2022]. 2022 (cit. on p. 29).

[49] Volkswagen Group News. *Volkswagen launches online sales*. https://www.volkswagen-newsroom.com/en/press-releases/volkswagen-launches-online-sales-7888. [Online; accessed 16-June-2022]. 2022 (cit. on p. 30).

[50] Volkswagen Group News. *NEW AUTO goes TikTok: Volkswagen Group debuts on video platform for digital natives*. https://www.volkswagen-newsroom.com/en/press-releases/volkswagen-launches-online-sales-7888. [Online; accessed 17-June-2022]. 2022 (cit. on p. 30).

[51] Filippo Einaudi. *Non solo auto: VW scommette sulle startup green a 360 gradi*. https://insideevs.it/news/545187/volkswagen-eit-fondo-europeo-innovazione/. [Online; accessed 17-June-2022]. 2021 (cit. on p. 30).

[52] AT Court. *Hedonic price indexes with automotive examples*. 1939 (cit. on pp. 31, 37).

[53] Allen C Goodman. «Andrew Court and the invention of hedonic price analysis». In: *Journal of urban economics* 44.2 (1998), pp. 291–298 (cit. on p. 32).

[54] Sherwin Rosen. «Hedonic prices and implicit markets: product differentiation in pure competition». In: *Journal of political economy* 82.1 (1974), pp. 34–55 (cit. on pp. 32, 37).

[55] James N Brown and Harvey S Rosen. *On the estimation of structural hedonic price models.* 1982 (cit. on p. 33).

[56] Harry W Richardson, Joan Vipond, and Robert A Furbey. «Determinants of urban house prices». In: *Urban studies* 11.2 (1974), pp. 189–199 (cit. on p. 33).

[57] George R Parsons. «Hedonic prices and public goods: an argument for weighting locational attributes in hedonic regressions by lot size». In: *Journal of Urban Economics* 27.3 (1990), pp. 308–321 (cit. on p. 33).

[58] Zvi Griliches. «3. Hedonic price indexes for automobiles: an econometric analysis of quality change». In: *Price indexes and quality change.* Harvard University Press, 2013, pp. 55–87 (cit. on pp. 34, 37).

[59] Zvi Griliches. «Notes on the measurement of price and quality changes». In: *Models of income determination.* Princeton University Press, 1964, pp. 381–418 (cit. on pp. 34, 37).

[60] Robert Halvorsen and Henry O Pollakowski. «Choice of functional form for hedonic price equations». In: *Journal of urban economics* 10.1 (1981), pp. 37–49 (cit. on pp. 35, 36).

[61] George EP Box and David R Cox. «An analysis of transformations». In: *Journal of the Royal Statistical Society: Series B (Methodological)* 26.2 (1964), pp. 211–243 (cit. on p. 35).

[62] Robert Halvorsen, Raymond Palmquist, et al. «The interpretation of dummy variables in semilogarithmic equations». In: *American economic review* 70.3 (1980), pp. 474–475 (cit. on p. 36).

[63] Allen C Goodman. «Willingness to pay for car efficiency: A hedonic price approach». In: *Journal of Transport Economics and Policy* (1983), pp. 247–266 (cit. on p. 37).

[64] Scott E Atkinson and Robert Halvorsen. «A new hedonic technique for estimating attribute demand: an application to the demand for automobile fuel efficiency». In: *The Review of Economics and Statistics* (1984), pp. 417–426 (cit. on pp. 37, 38).

[65] Mario Izquierdo Peinado, Omar Licandro, and Albert Maydeu Olivares. «Car quality improvements and price indices in Spain». In: *Estudios económicos/Banco de España, 72* (2001) (cit. on p. 38).

[66] Anna Matas and Josep-Lluis Raymond. «Hedonic prices for cars: an application to the Spanish car market, 1981–2005». In: *Applied Economics* 41.22 (2009), pp. 2887–2904 (cit. on p. 38).

[67] Hugo J Reis and JMC Santos Silva. «Hedonic prices indexes for new passenger cars in Portugal (1997–2001)». In: *Economic Modelling* 23.6 (2006), pp. 890–908 (cit. on p. 38).

[68] Henrik Andersson. «The value of safety as revealed in the Swedish car market: an application of the hedonic pricing approach». In: *Journal of Risk and Uncertainty* 30.3 (2005), pp. 211–239 (cit. on p. 38).

[69] Cumhur Erdem and İsmail Şentürk. «A hedonic analysis of used car prices in Turkey». In: *International Journal of Economic Perspectives* 3.2 (2009), pp. 141–149 (cit. on p. 38).

[70] Marc Prieto, Barbara Caemmerer, and George Baltas. «Using a hedonic price model to test prospect theory assertions: The asymmetrical and nonlinear effect of reliability on used car prices». In: *Journal of Retailing and Consumer Services* 22 (2015), pp. 206–212 (cit. on p. 38).