Erasmus University Rotterdam
Erasmus School of Economics
Data Science and Marketing Analytics
Master Thesis

Research into the tipping point from hybrid cars to EVs

Are hybrid cars running out of Dutch road?

T.P. Bakker (503875)

Supervisor:	dr. M. van Crombrugge
Second assessor:	dr. A. Alfons
Date final version:	October 30, 2023

Abstract

In this paper, the effect of the electric vehicles' rise on hybrid vehicle registrations is researched. The analyses use data from January 2007 until December 2022 from the Netherlands, a leading country in the transition to EVs. The reaction of hybrid registrations is examined using a vector autoregressive model containing six vectors. The other vectors include the registrations of EVs, the registrations of internal combustion engine vehicles (ICE), the GDP, and the electricity and gasoline prices. Six models are made. The first uses all data, while the following two differentiate between luxury and non-luxury brands. The last three models split the data on the type of owner. These types are private, business and the industry itself. The results indicate a rise in EV registrations to significantly negatively effect hybrid registrations in both the long and short term. However, a positive response of hybrids to an ICE shock combined with a negative response of ICE to a hybrid shock counter the negative effect. The prices of electricity and gasoline both significantly influence hybrid registrations. Electricity prices do so positively, whilst gasoline prices do so negatively. Comparing the responses of luxury and non-luxury brands shows the former to be inelastic and respond positively to EV shocks, which the latter does not copy. The different types of owners show clear variations in reaction, with the industry producing the most amount of significant responses. To conclude, the rise of EVs certainly is a challenge for hybrids. However, they will not disappear from the road soon due to their similar effect on ICE vehicles.

Keywords: hybrid vehicles, electric vehicles (EV), internal combustion engine vehicles (ICE), vector autoregression (VAR).

List of Figures

List of Tables

Contents

1 Introduction

Once hailed as the next big thing in the automotive sector (De Haan et al., 2006), hybrid cars are already being caught up by a new generation of vehicles: electric vehicles. Since its introduction in 1997, the Toyota Prius has been the best-selling hybrid car, with over 5 million units sold worldwide and a new model launched just last summer (Toyota Motors, 2022). However, due to an increasing desire amongst people to help the environment (Dekker et al., 2020), subsidies encouraging the purchase of fully electric cars (RVO, 2022) and laws being put into place prohibiting the sale of internal combustion engine (ICE) cars in the near future (Algemeen Dagblad, 2023), the life expectancy of the Prius and other hybrid cars might be cut short. In contrast, electric car companies like Tesla and Polestar are rapidly growing (Autoweek, 2023), whilst more and more traditional car companies like BMW and Mercedes-Benz are also adding fully electric vehicles to their line-up (Autoweek, 2022). This study aims to assess the current state of the hybrid car market in one of the world's leading countries in the transition to electric vehicles (Institute, 2023), where battery-powered vehicles now take a majority share in new car registrations (Autovista, 2023), being the Netherlands. The research aims to examine the relationship of hybrid registrations with the surging popularity of electric vehicles. Specifically, it seeks to explore if there is a downward trend in hybrid car registrations and to what extent this can be attributed to the rise in electric vehicle registrations. If no downward trend is identified, to what extent can the stability of hybrid car registrations be attributed to diminishing registrations of traditional internal combustion engine cars? Answering these crucial questions is vital for industry leaders in the €3.5-trillion automotive market (IBISWorld, 2023). Combining this all leads to the main research question being:

"What is the current state of the hybrid car market in the Netherlands, and how is it being impacted by the increasing popularity of electric vehicles?"

To research this, Dutch car registrations between 2007 and 2022 are examined. By analysing the registrations of all cars while accounting for numerous controlling variables, it is possible to comprehend the remaining lifespan of hybrid cars. The sub-questions used to determine a final answer include: "Can a downward trend be seen in hybrid registrations?", "Are registrations of electric vehicles cannibalising hybrid registrations, and are hybrid registrations cannibalising registrations of internal combustion engine cars?", "Does the gross domestic product affect this?", "Do various ownership models influence cannibalisation rates between vehicle types?", "Does the level of luxury offered by different brands affect their susceptibility to cannibalisation rates?" and "Do fuel prices, both gasoline and electricity, affect this?"

There are two main reasons why this research is of interest. The first reason is the need for more focus on (hybrid) cars in the existent literature regarding topics connected to this research, which will later be deliberated on. The second reason is the significant impact the findings could have on policies. If it is found that the consumers have surpassed the tipping point from hybrid cars to EVs, indicating their willingness to help the environment, this could influence the policies of both governments (Gadenne et al., 2011) as well as companies (Akerlof and Kranton, 2000) in Europe and worldwide. Governments could implement stricter rules, for example, by moving up the ban on selling ICE cars or coming up with more rigorous laws in other climate change fighting areas completely detached from the car industry, such as farming. They can do so knowing that the public will back them, as this research could provide more evidence that the public wants to protect the world's environment. The same goes for the policy of companies. If this paper discovers a consumer desire for eco-friendly products like EVs, companies could respond by incorporating more such products in their line-up, potentially making them more exciting and appealing for the average consumer, increasing the company's turnover and profits. Furthermore, this not only goes for car companies but for all companies, as long as there is a possibility to go greener in the product line-up. As climate change is one of the world's biggest problems right now, this research is very much socially relevant.

2 Literature review

This paper contributes to multiple streams of literature. This research taps into two main topics of literature: literature about the life cycle of products in general and diffusion of innovations and literature about sustainability, both for the consumers and the producers.

Product life cycle management is an essential factor in marketing. It entails managing a product from its very first idea to its retirement, as described by Stark (2022). When looking at cars as a product, they have a unique place in this type of management. Few products are as expensive as cars, yet owned by so many. A new car costs tens of thousands of euros, even up to tens of millions. However, there are over 1.4 billion of them in the world (TopGear Nederland, 2020), although this number is likely to be reduced in the coming decades according to the World Economic Forum (The Wall Street Journal, 2023). It is generally understood that product life cycles have gotten shorter over time, but not much empirical evidence exists for this, as found by Bayus (1998) and Bayus (1994). The higher innovation rate is a big reason for the supposed shorter life cycles. In the car industry, this innovation is EVs. When researching product cycles and innovations in the UK car industry, Holweg and Greenwood (2001) find indications for a clear trend of shorter life cycles. Whereas they, similar to MacDuffie et al. (1996) and Clark et al. (1991), research product variety within a car, e.g. if it has air conditioning or not, the present research focuses on the product variety in fuel type between cars. If this research finds evidence that hybrid cars are already running out of life, that would be another argument for the findings of Holweg and Greenwood (2001), which would be relevant for both the industry and the consumer. Another underexposed factor in this stream of literature is sustainability. The consideration of sustainability has frequently been overlooked in the process of new product development, despite the opportunity it provides to incorporate sustainable attributes throughout the product's life cycle (Gmelin et al., 2014). In other research by Gmelin and Seuring (2014), they interview six automotive companies and conclude that including sustainability increases the complexity of product life cycle management. Adding to the qualitative research already done is this quantitative research. Performing data-based analyses allows for seeing how managers are coping with this higher level of complexity.

Apart from the literature about the life cycle of products, this research also ties into the literature on the diffusion of innovations. As stated by Kaminski (2011), the adoption of a novel concept, service, method, philosophy, or other invention by individuals is called the diffusion of innovation. Despite being introduced over a century ago (Toews, 2003) and the theory being one of the most researched topics in behavioural science over the last decades (Rogers, 2010), very little recent research has been done looking at the diffusion of innovation in the major industry of cars. Three papers jump out when looking at the existing literature on the diffusion of innovation in the car industry. Using diffusion models to predict the market size of the emerging Chinese car market, Qian (2014) highlights the practical application of diffusion models for marketing managers in predicting car sales in the Chinese market, which predominantly consists of consumers who are relatively new to cars as products. Researching the US market, Lee (2018) utilises diffusion patterns observed in patent citations to examine the long-term sales of hybrid cars. Additionally, they explore the influence of interest diffusion, measured through web search traffic, on improving the short-term predictability of market sales for hybrid vehicles. As can be seen, these two papers focus on countries outside of Europe. In recent years, no significant quantitative research has looked at the diffusion of innovation in Europe. However, Nieuwenhuis and Wells (2003) does describe the diffusion of innovation in the car industry very well, highlighting the complex interplay of technical, economic, and social factors that influence the adoption and diffusion of new technologies. The authors note that various factors, including consumer preferences, government regulations, market competition, and supply chain issues, influence the adoption and diffusion of new technologies in the automotive industry. Whereas the research of Nieuwenhuis and Wells (2003) does not look at data but discusses both successful and unsuccessful instances from the past, there is still much to be written about this topic. Adding quantitative research to a stream of qualitative research enlarges the chances of identifying patterns (Linhares, 2019), allows for easier visualisation (Lee, 2010) and allows for more straightforward generalisation of the findings (Borgstede, 2021). There are many positive effects of quantitative research, alongside the vast amount of innovations that have taken place in the car industry, especially with the emergence of electric vehicles, making it an exciting addition to the existing literature.

When looking at the awareness of climate change amongst people, both Nisbet and Myers (2007) and Boykoff and Yulsman (2013) state that in recent decades, the media attention as well as the political debates about it have increased drastically, indicating an increase in overall awareness. Baiardi and Morana (2021) find that this is hugely connected to the per capita income in Europe. They state that wealthier countries are more likely to be aware of climate change. In the car industry, from a consumer perspective, awareness of climate change is shown in the sales of less-emitting cars like EVs, as EVs are known to be better for the environment than traditional ICE cars or newer hybrid cars. However, the greater awareness of climate change does not directly influence consumer behaviour, as found by Venghaus et al. (2022). In their German case study, they researched three sectors, one of which is the general mobility sector. Despite the significant increase in awareness, they could not find any notable behavioural changes. This research adds to the existing literature about this topic by seeing if any significant change in purchasing can be perceived when looking at the primary industry of cars specifically and if this change is more prominent for the more affluent countries.

Not only the public's awareness of climate change but also the awareness within the car industry is of interest to this research. BloombergNEF (2022) states that in 2021 alone, 12 major car manufacturers announced to completely phase out internal combustion engines, some as soon as 2026. Furthermore, even more manufacturers announced either stopping investing in ICE cars or having net-zero targets around the year 2050. When looking at the American car industry, Penna and Geels (2015) find that consumer pressure forces American automakers to focus on and invest in low-carbon technologies. Whereas previous research such as Dijk et al. (2016) was unsure of the potential of electric vehicles, the recent rise in EV sales and the focus of car manufacturers themselves might suggest otherwise. This research is relevant for the above papers as it gives car manufacturers a clear indication of whether they should keep investing in technologies other than EVs and because it will show whether or not EVs live up to their potential.

Apart from the reasons already mentioned, there is something else this paper adds to the existing literature. Whereas all car-focused research in the topics above focused only on pure ICE cars or the car industry in general, far less research has been done on hybrid cars, especially in recent years. However, as hybrid cars make up about 22% of the total car registrations, according to the European Automobile Manufacturer's Association (ACEA, 2023), they are still very relevant and still need to be researched.

3 Conceptual framework

As previously mentioned, significant changes have occurred in the car industry over the past few decades, particularly concerning vehicle engine types. In order to provide a comprehensive overview of the precise nature of these changes over time, the figure below illustrates the evolving market landscape during various periods. This visual representation offers valuable insights into the transformation of the automotive industry.

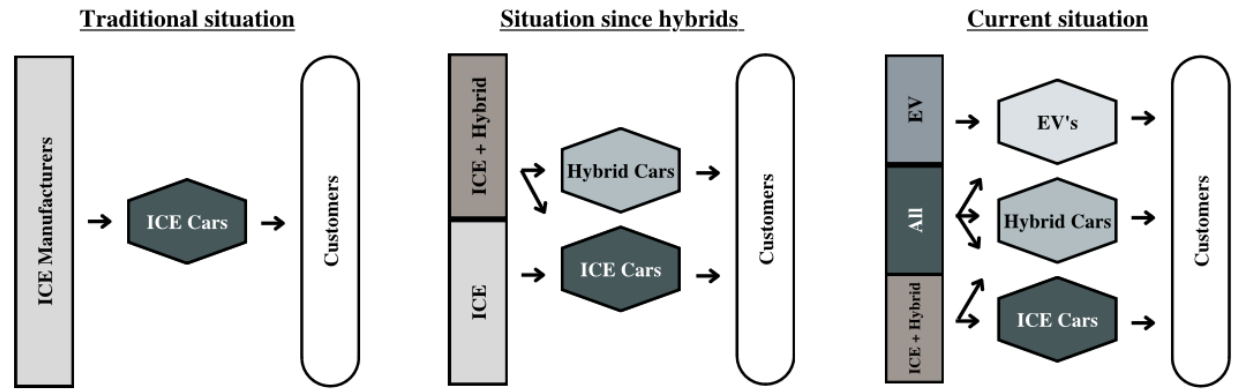


Figure 1: Cars produced in different situations

The figure shows the market situation for three different moments: the traditional situation, the situation after the introduction of mass-produced hybrid cars and the current situation. Each time, the left side shows what cars the manufacturers produce, the blocks show the types of cars available, and the right side shows the customers. The object sizes in the figure do not necessarily correspond to their market share. As seen in the traditional situation, all manufacturers solely produced ICE cars. After introducing the first mass-produced hybrid cars, the situation changed as some manufacturers were producing both hybrid and ICE cars, while others still only produced ICE cars (CarsDirect, 2022). No major car manufacturers solely produce ICE cars anymore, as even classical racecar manufacturers like Lamborghini are introducing hybrid cars (Autoblog, 2022). However, some companies solely produce electric vehicles, such as Tesla (Tesla, 2023), whilst other manufacturers like BMW produce all three types of engines (BMW, 2023).

The main model used in the research to examine how the current situation is expected to change is a vector autoregression (VAR) model. The model consists of six vectors in total, all deliberated on in table 1. The six vectors used in the model are both in number and contents comparable to other VAR models used when researching car sales.Konstantakis et al. (2017) uses a six-vector model when exploring Greek auto sales, and Fernandes and Dantas (2020) use just five vectors to examine monetary policy's effect on Brazil's car sales. Especially Konstantakis et al. (2017) use similar vectors, also using car sales, GDP and fuel prices in their models. Similarly, Fernandes and Dantas (2020) use car sales and GDP as vectors in their model. The vectors are shown in table 1.

Table 1: Vectors in models

Name	***Short***	***Definition***	***Endogenous***	***Exogenous***
		Main vectors		
Hybrid registrations$_t$	Hyb_t	Number of new hybrid cars registered at time t	×	
ICE registrations$_t$	Ice_t	Number of new ICE cars registered at time t	×	
EV registrations$_t$	EV_t	Number of new EV's registered at time t	×	
Gasoline price$_t$	Gas_t	Price of a liter of fossil fuel at time t		×
Electricity prices$_t$	Elc_t	CPI of electricity per kWh at time t, 2007 = 100		×
GDP$_t$	Gdp_t	Percental growth of gross domestic product at time t		×
		Other variables		
Laws$_t$	Law_t	Dummy variable equal to 1 when there is a law promoting EV sales at time t, else equal to 0		×
Subsidy$_t$	$Subs_t$	Dummy variable equal to 1 when there is a subsidy promoting EV sales at time t, else equal to 0		×
Interest$_t$	Int_t	Differenced interest on 10 year government bond		×
Infrastructure$_t$	$Infr_t$	Number of charging stations at time t	×	
Type of car$_t$	Typ_t	Dummy variables, 0 when a personal vehicle, 1 if van	×	
Inflation$_t$	CPI_t	Differenced monthly inflation rate in the Netherlands	×	

Notes: The table shows the variable names, their abbreviation, their meaning and whether they are exogenous or endogenous as used in the models. The variables are split up into main vectors and control variables.

The first three vectors are obviously endogenously related, but this is something a VAR model can cope with, according to Pauwels (2017). The model assumes that the variables are endogenous, meaning they are influenced by each other and that the shocks or disturbances to the system are correlated. The VAR model captures the dynamic interrelationships between the variables and can be used to forecast their future values. To estimate a VAR model, one needs to specify the appropriate order p, reflecting the number of lags used in the estimations. The estimated coefficients can then be used to forecast the future values of the variables, as this is also something the VAR model is capable of doing, according to Anderson (2011). He illustrates this by testing the model on Monte Carlo and empirical settings. Monte Carlo settings are an excellent tool for analysing the potential impact of changes (Back, 1995). According to Anderson (2011), the factors within a VAR model are expressed as observables resulting from linear combinations of lagged levels and lagged differences. Consequently, these observable factors possess the potential for forecasting, he says.

The main variables of interest in these analyses are the total number of new registrations for different fuel-type cars per month in the Netherlands. However, a VAR model also requires many control variables, which are shown in table 1. These variables include both exogenous and endogenous variables. Please note that the endogenous control variables are treated as vectors in the model, which differs from their exogenous counterparts. The exogenous control variables exist of the legislation, subsidies, and interest. The endogenous control variables include the type of car (van or personal vehicle), the infrastructure of charging stations, and inflation. Inflation might seem exogenous at first glance, but according to Times (2023), car sales do influence inflation, where it is evident that the reverse is also true (CNBC, 2023). Especially controlling for infrastructure is interesting, as Ma (2020) find that increasing the number of charging stations significantly increases the number of EVs sold, whilst the same cannot be said for sales of (plug-in) hybrids. Therefore, controlling for the amount of charging poles in a country will likely improve the models vastly. The same goes for the variables of laws and subsidies. Azarafshar (2020) find that in Canada, a financial incentive of \$1000 in the form of either subsidy or tax discounts raises the sales of EVs between 5% and 8%. This indicates that laws and subsidies influence the sales of EVs, which, therefore, means that these variables should be controlled for. The control variables are also shown in the above table, split into exogenous and endogenous control variables, to give a clear overview.

In total, six different models are made. The first model looks at the dataset as a whole without making any differentiation between brands or anything. The following two models examine differences between brands, focusing on the supply side of the market. The final three models analyse different types of buyers, focusing on the demand side of the market. Investigating both sides of the market and the market as a whole establishes a comprehensive view, which adds value to the findings. Table 2 provides definitions for each moderator.

On the supply side, the data is split upon the luxury of the car brands. In order to split the brands into luxury and non-luxury, the Kelley Blue Books (KBB) reports are used as a source (KBB (2023) & KBB (2023)), alongside some own experience for brands not included in these reports. KBB is a widely-recognised resource in the United States for determining new and used vehicle pricing. In the end, 39 manufacturers are classified as luxury, whilst 42 are classified as non-luxury. Table 11 in the appendix presents each brand's classification, source, sales figures, and ranking. There are two reasons to split based on luxury. When buying cars, some of the most important factors are safety, quality, comfort and design (Statista.com, 2022). These factors are aspects in which luxury cars

Table 2: Different models

Number	***Name***	***Short***	***Definition***
		Total	
1	Complete	*All*	The whole dataset, no differentiation.
		Supply side	
2	Luxury	*Lux*	Model only looking at luxury car brands, as classified by either Kelley Blue Books or own experience.
3	Non-luxury	*Non*	Model only looking at non-luxury car brands, as classified by either Kelley Blue Books or own experience.
		Demand side	
4	Private	*Priv*	Cars bought by private people for their personal use, as classified in the data.
5	Industry	*Indu*	Cars bought by the industry itself, such as rental companies, as classified by the data.
6	Business	*Buss*	Cars bought by non-industry companies, as classified in the data

Notes: In the table all six models are given. The table shows their number, name, abbreviation and definition.

excel (Kelley Blue Books, 2021), making them a suitable moderator for this research. The second reason to have luxury as a moderator is because, generally speaking, luxury goods are found to be more sustainable (Sun et al., 2021), despite luxury often being blamed for hampering sustainability (Aliyev et al., 2019). This research offers a valuable opportunity to investigate whether the perceived heightened sustainability associated with luxury goods translates into a swifter adoption of environmentally beneficial innovations by luxury brands compared to their non-luxury counterparts.

When examining the market from the demand side, the data is split based on the car owners' types. There are three types of owners: private, business and industry. The private group encompasses all registrations made by individuals, whether through a purchase or a personal lease. The same goes for the business owners, with purchases and business leases counting towards this group. The final type of owners consists of the car industry itself. This group comprises the rental companies and vehicle industry labels in the data. The differentiation between individuals and companies is made because, for businesses, public opinion is essential (Nicholson and Robertson, 1996). The companies want to be sustainable (Vintró et al., 2014), partly because the company's image is reinforced significantly, and this can have a lasting effect on the company's competitive position in the market (Malancea, 2022). Buying EVs instead of ICE or hybrid cars allows companies to showcase their desire to act environmentally friendly. For individuals, other factors besides sustainability play important roles when buying a car (Statista.com, 2022), making it interesting to research whether companies adapt to EVs quickly.

As a summary, figure 2 visually represents the conceptual framework, depicting the model with all its vectors and moderators. This visualisation serves as a tool for better understanding and analysis of the model's relationships and dynamics.

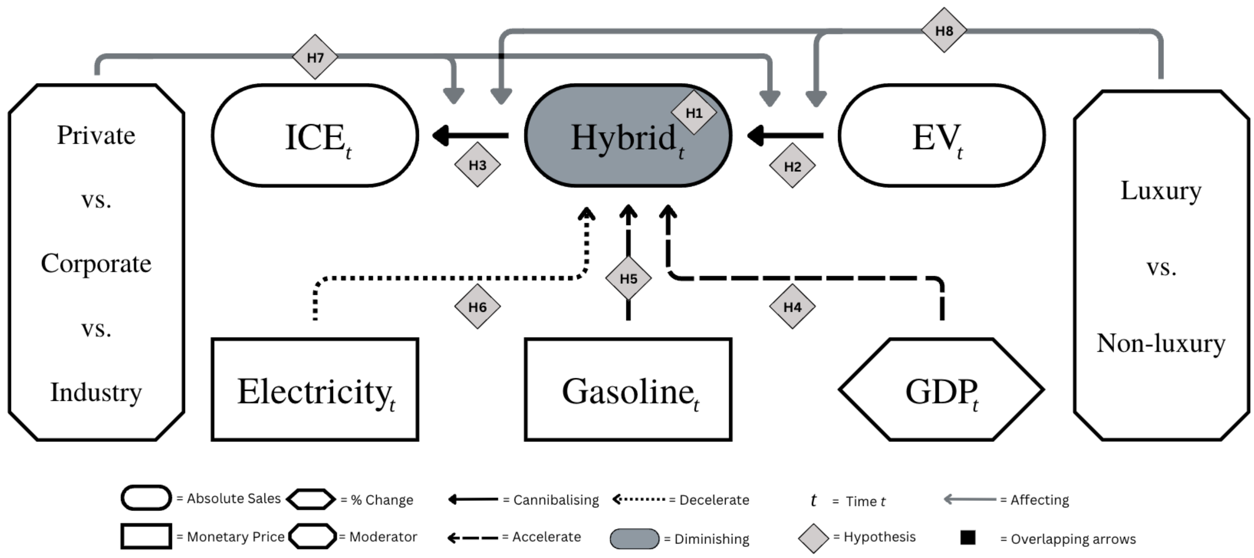


Figure 2: Visualisation of conceptual framework

The registrations for ICE cars, hybrid cars, and EVs are on the top. Below are the exogenous vectors. The arrows' colour and direction show the relationship between the variables researched. Only researched relations are depicted by a line. Other potential relationships are ignored and, therefore, not shown in the figure. On the two sides of the figure, the moderators are shown. On the left are those of the demand side, and on the right are those of the supply side. Different shapes in the figure describe different types of variables.

Besides the variables, the hypotheses are also depicted in the above image. The first hypothesis talks about the overall registrations of hybrid cars. With the increase in EV sales (Autoweek, 2023), the upcoming ban on internal combustion engines (Algemeen Dagblad, 2023), the rise in climate awareness among consumers (Dekker et al., 2020) and the multiple types of subsidy given out by governments to increase EV sales (RVO, 2022), it is to be expected that other cars besides EV's are seeing a decrease in registrations. Formally put, this leads to the following hypothesis:

Hypothesis 1: Registrations of hybrid cars are diminishing.

The substantial increase in EV sales (Autoweek, 2023) requires examining their source, as such sales cannot materialise out of thin air. From a broad perspective, two customer types can contribute to the growth in sales for any product (Sinkinson, 2015). Firstly, some new customers were previously inactive participants in the market. In the context of EVs, these customers represent individuals or organisations that previously lacked interest in purchasing a car but are now considering buying one. Motivations for these new customers may vary but include factors such as the environmental benefits of reduced vehicle emissions or how they look. The second type of customer that can lead to new sales is a customer who switches from a competitor. These customers were already in the market, or in this case, were already looking for a car but decided to switch from an ICE car or a hybrid to an EV. This could be because the customer might have been dissatisfied with the previous brand or product or reasons similar to why a new customer would join the market. To see whether or not this second type of customer is significant in increasing EV registrations, the second hypothesis is:

Hypothesis 2: EV registrations are cannibalising hybrid registrations.

If hypothesis one turns out to be false whilst hypothesis two turns out to be true, this begs the question of where the new hybrid registrations originate. In this case, hybrid registrations are not diminishing despite being cannibalised by EV registrations, meaning that new registrations are replacing the registrations eaten up by EVs. Also, in this case, there are two potential types of customers where these new registrations could originate from (Sinkinson, 2015). It could be new customers coming into the market who want an environment-friendly car but are afraid of buying an EV. According to Tarei (2021), some of these potential fears are too short of a range, a lack of performance and a shortage in infrastructure. On the other hand, the new registrations could stem from customers who previously drove ICE cars, who are now looking for something else but have the same fears as mentioned by Tarei (2021). Knowing which type of customers account for these registrations is an important factor when planning new marketing strategies and should be examined. In order to assess the significance of the second type of customers in contributing to the potential new hybrid registrations, the hypothesis considered is:

Hypothesis 3: Hybrid registrations are cannibalising ICE registrations.

Following an analysis of the registration dynamics, it is now appropriate to explore the potential factors that impact the variations in the volume of registrations. To start, the effect of the gross domestic product is examined. As found by Sarmento (2016), a higher GDP per capita leads to more money spent on consumption. When looking at the different fuel types of cars, electric vehicles are generally more expensive than ICE or hybrid cars (CarsDirect, 2023). Given these factors, it is plausible to think that with a higher GDP per capita, consumers are quicker to transition to EVs, potentially resulting in a more rapid decline in hybrid vehicle registrations. In light of this, the next hypothesis is formulated as follows:

Hypothesis 4: GDP is positively connected with diminishing hybrid registrations.

The other two factors potentially influencing the fluctuations in registration volumes researched are the two primary sources of fuel used by cars: gasoline and electricity. Specifically, the effect of the prices of these fuels on the registrations is explored, commencing with the traditional gasoline fuel type. Burke (2012) researches the effect of higher gasoline prices on consumer behaviour. The results indicate that higher gasoline prices induce consumers to substitute for more fuel-efficient vehicles. As hybrid cars are typically more fuel efficient than their ICE counterparts (Awadallah, 2018), gasoline prices emerge as an additional potential determinant affecting the sales of hybrid vehicles. In this scenario, higher prices would likely lead to a positive change in registrations, thus formulating hypothesis 5 as follows:

Hypothesis 5: Gasoline prices are positively connected with diminishing hybrid registrations.

Where Burke (2012) researches the effect of gasoline prices on consumer behaviour and ICE car registrations, similar research is done on the effect of electricity prices. Soltani-Sobh (2017) reveals comparable findings in their analysis of the effect of electricity prices on electric vehicle (EV) sales. The study establishes a significant relationship between electricity prices and the adoption of EVs. However, there is also another side of the story, as Olivella-Rosell (2014) finds EVs to influence electricity prices significantly. Electricity prices generally affect EV sales more than hybrid sales. This is primarily because hybrids, which utilise both gasoline and electricity, are not solely reliant on and use less electricity for their operation, causing them to be less influenced by fluctuations in electricity prices. This could lead to EV registrations cannibalising hybrid registrations less when energy prices increase. Formally put into a hypothesis, the following is presented:

Hypothesis 6: Electricity prices are negatively connected with diminishing hybrid registrations.

The final two hypotheses focus on the model's different moderators, starting with the different types of ownership. As mentioned, companies care about public opinion (Nicholson and Robertson, 1996), which in the modern era leads to them wanting to be sustainable (Vintró et al., 2014). Not only does this have a lasting positive effect on the market position of the company (Malancea, 2022), it also has a positive effect on the financial performance of the company (Chen et al., 2018) in the long term. Companies want to have a long-term focus, as this in itself also betters their financial performance (Doyle and Hooley, 1992), and it leads to a superior value of the company (**?**). This all suggests it is beneficial for the company to quickly adapt EVs into their fleet. These reasons do not apply to individuals, as there are other more important factors for them when purchasing a vehicle (Statista.com, 2022). Therefore, it would be expected to see a different reaction between individuals and companies on the introduction of EVs, which formally leads to the following hypothesis:

Hypothesis 7: The various ownership models impact cannibalisation rates distinctly.

On the market's supply side, luxury brands are expected to have a quicker transition to EVs than non-luxury brands. Luxury brands are known to be better in safety, quality, comfort and design (**?**). Luxury manufacturers are always aware of and keen to introduce innovations (Pantano et al., 2018). In the car industry, this innovation is the introduction of the EV. Developing these innovations also leads to the company having higher customer satisfaction and loyalty (Woo et al., 2021). One thing distinguishing luxury companies the most from their non-luxury counterparts is uniqueness (Heine and Phan, 2011). Early adoption of new technologies thus leads to the company having a more luxurious image, which is very important for the company (Nicholson and Robertson, 1996). These reasons all suggest that it is the luxury companies that react first to the innovation of EVs, which leads to the final hypothesis:

Hypothesis 8: The differing degrees of luxury brands offer distinctively affect cannibalisation rates.

Combining these eight hypotheses offers a promising approach to address the central research question. Employing a VAR model, well-known for its ability to effectively handle endogenously related variables, such as the registrations of different fuel types of cars, allows for accurate future forecasting. The model incorporates six vectors, ensuring the inclusion of the most crucial variables. Additionally, with five control variables encompassing both endogenous and exogenous factors, potential confounding effects are minimised, ensuring the inclusion of significant factors. Moreover, the creation of six distinct models enables the generation of a comprehensive and informative snapshot of the current state of the market.

4 Data

This study uses a combination of economic and energy-related variables from January 2007 to December 2022. The dataset consists of four key components: car registrations, gross domestic product (GDP), fuel costs and electricity prices. The car registration data offers insights into consumer behaviour and the automotive industry's performance over the specified period. Subsequently, the study presents information on GDP to offer a broad understanding of economic growth and development trends. Furthermore, the fluctuations in gasoline costs over time are described. Lastly, the data on electricity prices is presented, shedding light on the energy sector dynamics during the study duration. Each data component will be analysed profoundly, and some visualisations will be given, starting with the car registrations.

4.1 Car registrations

The central part of the data, the car registrations, is provided by Toyota Nederland. The data consists of all new registrations of cars per month per model of car. Numerous variables are given with each entry. These are all shown in the table 3 below. The meaning gives a brief explanation of what the variable represents. The bold and underlined variables are used in the models. Others might be used as control variables or moderators.

The data set contains 480.326 rows representing 8,043,640 new cars registered. As shown in figure 3, the highest month was January 2011, with 82,566 new registrations. It is unsurprising that January is the highest month, as a big spike can be seen in most years. In the car sector, January is genuinely known to be the best month for registrations, whereas the worst months come at the end of the year (Autoverleden.nl, 2014). Predicatively, the slowest month in the data set is a December, namely the December of 2008. In this month, only 8,875 cars were registered. Overall, a slight decline in car registrations is shown in the data set, depicted by the red line in figure 3.

The data's overall distribution of fuel types is still very skewed towards the classic ICE cars. About 86% of the cars, or just less than 7,000,000, registered between January 2007 and April 2023, contained an internal combustion engine. Hybrids only account for around 8%, or about 650,000 cars, whereas EVs only make up 5%, or around 370,000 cars. There is 1% of the registered cars classified as other. These cars are the ones using hydrogen or other infrequently used fuels. These cars are to be ignored in the analyses.

Table 3: Variables in raw registrations data.

Variable	*Meaning*	*Options*
Soort voertuig	Vehicle type	Passenger car, Van
Segment level 1	First segment level	Passenger car, Van
Segment level 2	Detailed segment level	A-segment, B-MPV, B-premium, B-segment ...
Merk	Car brand	Aiways, Alfa Romeo, Alpine, Aston Martin, Audi ...
Model	Car model	01, 1, 1-serie, 1007, 108, 110, 111, 112, 124 ...
Merk.Model	Brand and model	Aiways U5, Alfa Romeo 4C, Alfa Romeo 8C ...
Soort eigenaar 1	Type of owner 1	Big business, Fleet, Lease company, Private ...
Soort RTL	Registration of leases	No RTL, Big business, Private, Small business
JaarMaand	Year and month	200701, 200702, 200703, 200704, 200705, 200706 ...
Maand	Month	Ranging from January through to December
Brandstof	Fuel	BioFuel, CNG, Diesel, Full EV, Hybrid, LNG ...
EV concept	Type of EV	BEV, FCEV, HEV, MEV, Not applicable ...
Jaar	Year	Ranging from 2007 through to 2023
Aantal	Amount	Ranging from 1 through to 8459
EV/NON-EV	Engine type	EV, Non-EV
Soort Eigenaar	Type of owner 2	Business buy, Business lease, Private buy ...
Segment level 3	Less detailed segments	A-segment, B-segment, C-segment, CDV ...
Segment level 4	Different segmentation	Mainstream, Premium
Samenwerkingsverband	Partnership	No, Ford-Volkswagen, Geely, Renault-Mercedes ...
Kwartaal	Quarter	Q1, Q2, Q3, Q4
YTD	Year-to-date	No, Yes

Notes: The table shows the variable names, their meaning and the options for all variables from the data set containing the registrations in the Netherlands. The options are shown in alphabetical order, with only the first few shown when there are too many options to fit in the table.

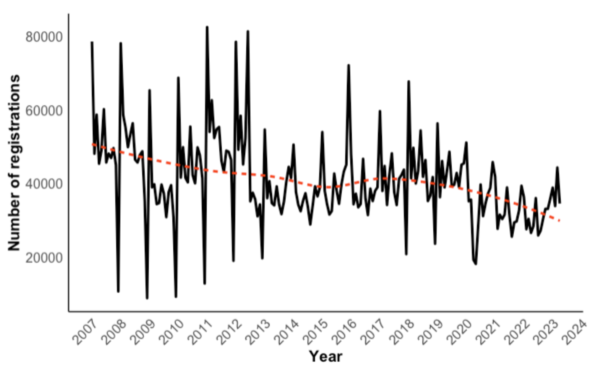


Figure 3: Monthly number registrations

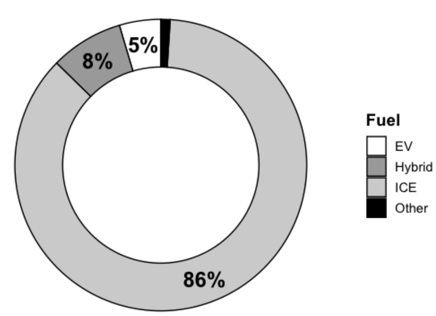


Figure 4: Distribution of fuel types registered

By examining the yearly distribution of fuels in new car registrations, a different picture is illustrated, one that complies with the changes in industry proposed in figure 1. Figure 5 shows that whereas ICE cars made up basically the whole market at the beginning of the covered period, they have only recently lost their status as an absolute majority. In 2007, ICE cars still made up 98% of the registration, but in recent years, this percentage has rapidly declined and is failing to reach the 50% mark. Hybrid cars have been on the rise for a long time. In 2007, only 3,129 hybrids were registered, but through slow and steady growth, they now account for nearly a third of the market.

This growth seems to have slowed down a bit, as since 2021, the share of hybrids has only increased by about 20%, whereas EVs saw a growth of around 50%. The registrations of EVs have had to come a long way. In 2008, only eight new electric vehicles were registered, but now they make up nearly a quarter of the total market. Again, the other fuel types play no significant role.

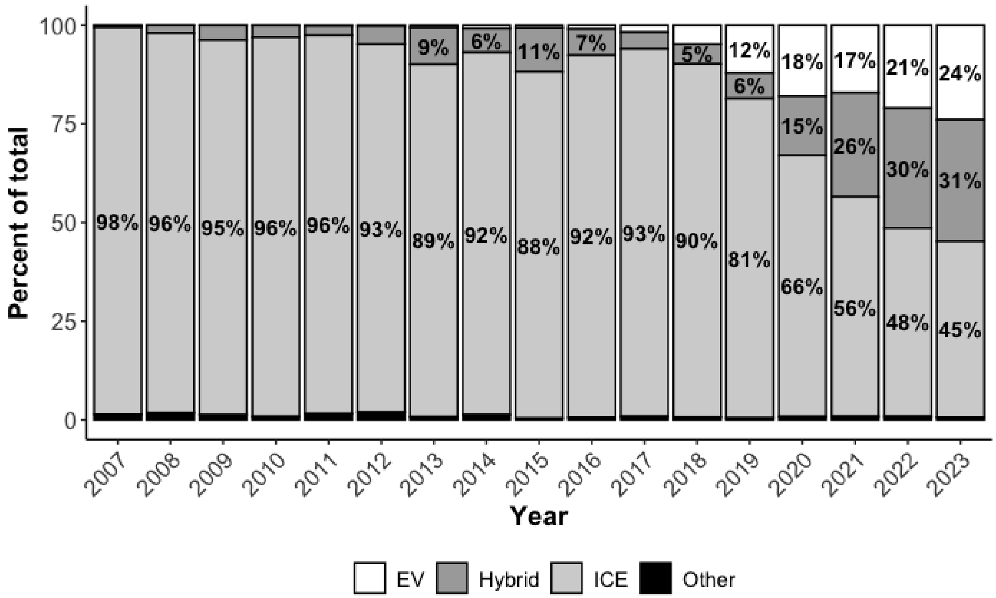


Figure 5: Yearly distribution of fuel types registered

The distribution between the different moderators and the spread of fuel types within the moderators is shown in table 4 below. On the supply side, the non-luxury are clearly bigger than their luxury counterparts. However, the luxury brands seem to be further in the adaptation of EVs and hybrids, seeing their relative higher percentages. On the demand side, it is seen that the private and businesses are similar in size. But again, the smallest one, in this case, the industry, has the relatively highest percentage for EVs and hybrids.

Table 4: Distribution between moderators

Name	***% of Total***	***% ICE***	***% Hybrid***	***% EV***
		Supply side		
Luxury	17.9%	10%	12%	78%
Non-luxury	82.1%	3%	8%	89%
		Demand side		
Private	38.5%	3%	7%	90%
Industry	18.1%	7%	9%	84%
Business	43.4%	3%	8%	89%

Notes: The table shows the distribution of luxury versus non-luxury brands and the different type of owners in terms of registrations of total. The distribution of fuel types within the moderators are also shown, rounded up to the nearest integer.

4.2 Gross domestic product

The other data sets come from the Centraal Bureau voor Statistiek (CBS), the leading organisation in the Netherlands for societal data. The data set used contains the GDP per quarter of the year since 2006. In figure 6, however, the yearly GDP is depicted, as this is visually more pleasing. Overall, the lowest GDP was seen in 2009 at a yearly level of 655,964 million euros. When looking at the quarterly level, the lowest point is also found in the third quarter of 2009 (160,301 million euros). The highest GDP turns out to be in 2022 on a yearly level, with it being 806,410 million euros, which is around 23% higher compared to 2009. On a quarterly level, the highest GDP is 207,629 million euros, seen in the last quarter of 2022. Overall, apart from downward spikes with the crises in 2008 and COVID-19, the GDP steadily grows, as depicted by the dashed red line.

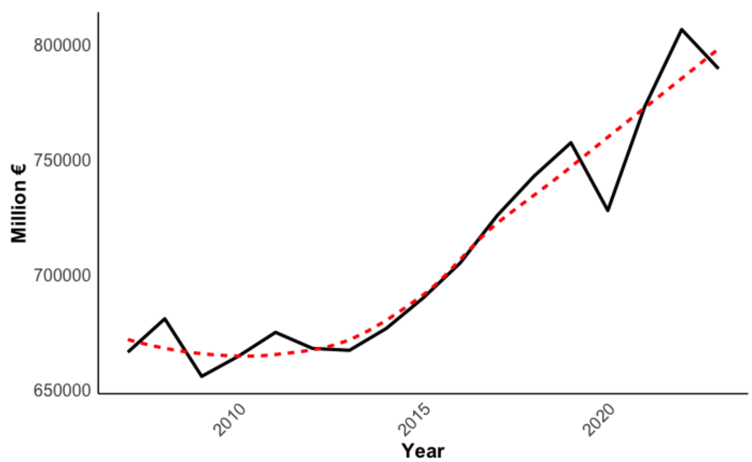


Figure 6: Dutch GDP per year

4.3 Fossil fuel prices

The next data about fuel prices is also downloaded from the CBS. Two primary fuel types are used in ICE cars: gasoline and diesel. There is no need to go into the technical difference between the two, but seeing as they are equally distributed in the dataset (53% gasoline, 47% diesel), both need to be shown. The dark grey line in figure 7 shows the daily historical price of gasoline in euros per litre in the Netherlands since January 1^{st} 2006, and the black line does so for diesel. The red line depicts a weighted average of the two fuels, using the weights mentioned before. The lowest prices for both fuels are around New Year's Eve from 2008 to 2009, with the lowest average of €1.048 found on December 30^{th} 2008. The highest prices are seen in March 2022, with the maximum average being €2.333 on March 20^{th}. Generally speaking, the price of gasoline has always been higher than that of diesel. Apart from 84 days in the second half of 2022, diesel has always been the more expensive fuel per litre.

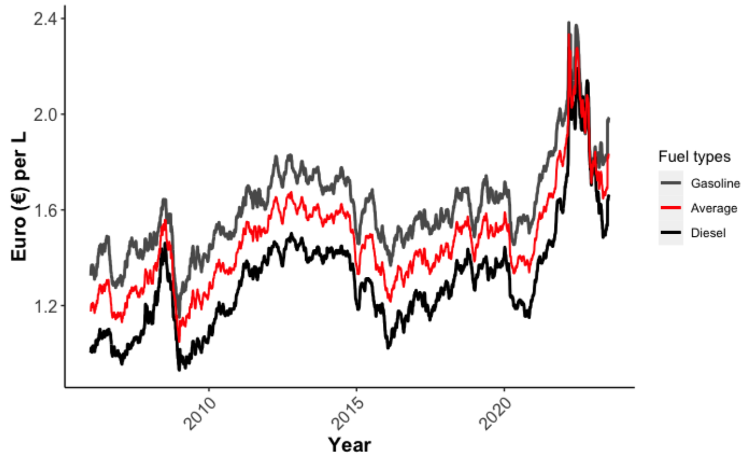


Figure 7: Line of daily fossil fuel prices

4.4 Electricity prices

The final data set used pertains to the electricity prices and has also been sourced from the CBS. This data is required as electricity is to EVs, what gasoline and diesel are to ICE cars. The CBS provides data on both household and non-household prices. It then divides the prices into different groups based on the total electricity usage per year. The data shown in figure 8 is the household prices for the usage group of 2.5 - 5.0 MWh per year. This category is chosen because the average household uses between 2.1 and 3.3 MWh per year (PureEnergie.nl, 2023), which means most households will pay these prices. The prices shown include tax and VAT and are depicted as the transaction price in euros per kWh. As seen in figure 8, the price of electricity has been stable for large parts of the data set. Only since COVID-19 hit, large changes in prices are perceived. Directly after COVID-19 hit, the prices dropped, and now a significant upward spike is shown.

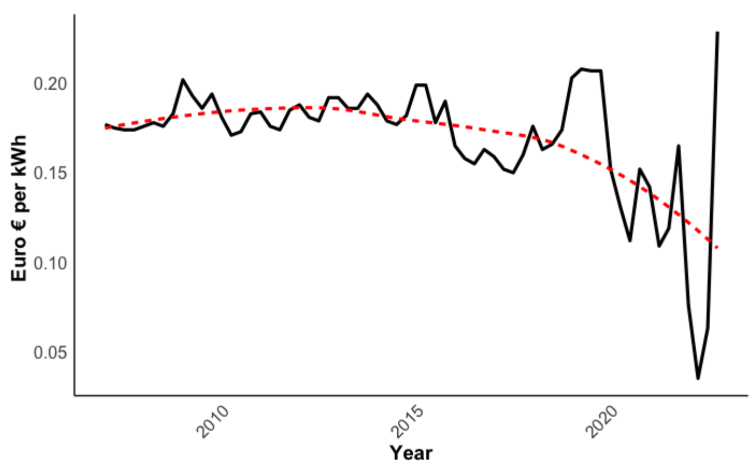


Figure 8: Line of monthly kWh price

4.5 Control variables

For the controlling variables laws, subsidy and infrastructure data is needed that is not in the original registrations dataset. The infrastructure variable talks about the number of charging stations there are. In the Netherlands, this data is maintained by the Rijksdienst voor Ondernemend Nederland (RVO). Upon request, they provided the total number of charging poles in the Netherlands from 2009 until 2023. According to Athlon (2023), a major Dutch leasing company, there will be 1.7 million charging stations in the Netherlands by 2030. The below figure shows the total number of charging poles for each year in the Netherlands.

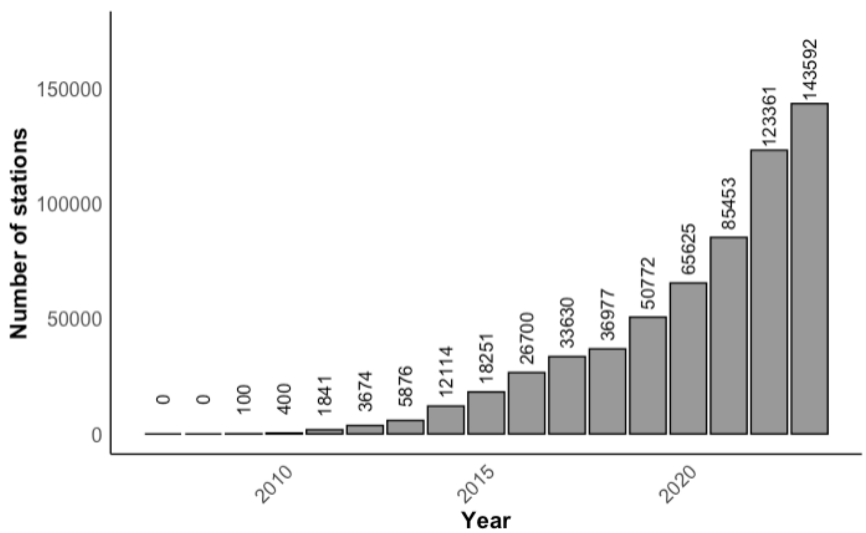


Figure 9: Number of charging poles in the Netherlands over the years

The figure shows the number of public charging stations in the Netherlands from 2007 until August 2023. Private charging stations are ignored in the research. The Netherlands' first charging station was built in 2009 in Tilburg (ElaadNL, 2011). Since then, the number of charging stations has rapidly increased, as seen in figure 9. Where in the beginning, only a few hundred or thousand new stations were built per year, the last few years have seen tens of thousands of charging stations being built each year. The most recent number shows 143,592 public stations in the Netherlands. With this, about 30% of all charging stations in Europe are found in the Netherlands (ACEA, 2022), showing that the country is one of the front runners in providing infrastructure for the transition to EVs. Even when looking at the number of stations per 100 thousand inhabitants, the Netherlands is one of the forerunners. Only Norway and Luxembourg beat the country (Statzon, 2023), substantiating that the Netherlands is leading the way in helping the transition to EVs.

When looking at the laws and subsidies promoting EV purchases, there are three factors to focus on in the Netherlands. Two of those, the Belasting van Personenauto's en Motorfietsen (BPM) and the motorrijtuigenbelasting (MRB) are considered to be laws, whilst the third factor of Subsidieregeling Elektrische Personenauto's Particulieren (SEPP) is considered to be a subsidy. MRB is a tax imposed on motor vehicles, typically based on factors such as vehicle type, engine size, and emissions, and it is used to generate revenue for the government to fund transportation infrastructure and services (ANWB, 2023b). In the Netherlands, EVs are completely exempt from this tax from 2017 until 2024 and will have a 75% discount for 2025 (ANWB, 2023b). BPM is a tax on passenger cars and motorcycles in the Netherlands, calculated based on the CO2 emissions and the vehicle's net list price, to be paid when purchasing the car (ANWB, 2023a). From 2013 to 2024, Dutch EVs are exempt from the starting rate, and because of the zero-emission, they do not need to pay anything (ANWB, 2023a). SEPP is a subsidy program in the Netherlands designed for individuals who purchase or lease new fully electric vehicles. It aims to incentivise the adoption of electric cars and promote sustainable mobility by providing financial assistance to eligible private buyers or lessees. Since 2017, the government has provided a money pot at the beginning of the year for new EV buyers to use when purchasing a car. The total amount of money in the pot and available per buyer changes yearly. How much was available for what year can be seen in table 9 in the appendix. The below figure shows when each policy was active.

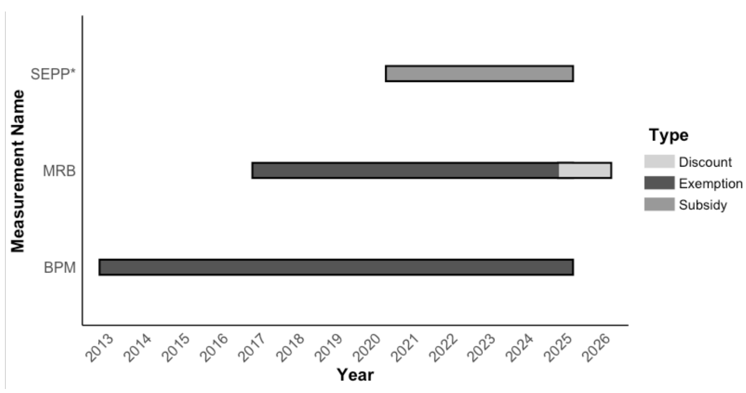


Figure 10: Timeline of government measurements

The final two variables presented are the interest and inflation rates in the Netherlands over the past 15 years, depicted in figures 11 and 12, respectively. Figure 11 depicts the interest on a 10-year government bond in the Netherlands. The interest is shown as a decimal number, with the red dashed line again showing the trend. An apparent downfall of interest was perceived up until COVID-19 happened. At that moment, the interest flattened out before skyrocketing back up. This should be no surprise to anyone who has followed the news in recent times (RTL Nieuws, 2023).

* The money pot for SEPP might have been empty before the end of the year, but this is not depicted.

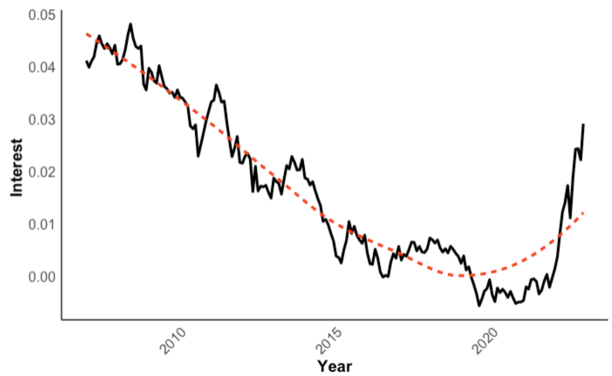


Figure 11: Interest on 10-year bonds.

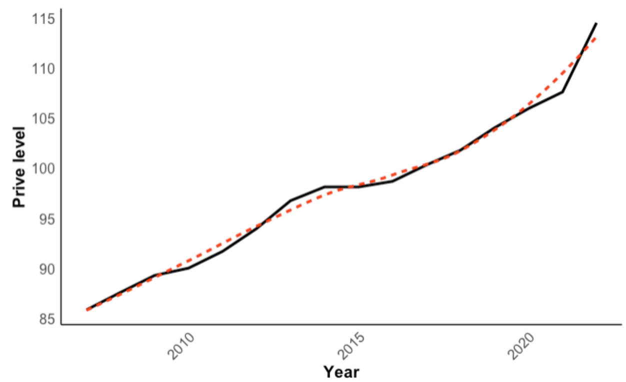


Figure 12: Price level over the years.

Also, in the inflation graphic, a clear trend can be seen, but this time, just a nearly straight upward trend. The figure presents the price level in the Netherlands, with 2015 being equal to 100. The dashed red line again indicates the trend in the data, although it hardly differs from the original line this time. The graph shows a pretty steep price increase, with the price level in 2022 (124.96) being nearly 50% larger than that of 2007 (85.89), giving an average growth of 2.4% per year.

5 Methodology

This section comprehensively examines the vector autoregressive (VAR) model and its fundamental components. Firstly, the model itself is explained alongside how the best number of lags p is selected. Subsequently, the Granger causality test is elucidated, facilitating the identification of causal relationships between variables. Lastly, the impulse response analysis, which investigates the dynamic effects of shocks in the VAR model, is explained. This thorough exploration aims to comprehensively understand the VAR model and its applications in analysing intricate systems.

5.1 VAR(p)-model

As already mentioned, the primary model used for the analyses in this research is a vector autoregression model (VAR model). VAR is a multivariate forecasting algorithm used when two or more time series variables mutually influence each other. Unlike other autoregressive models like AR, ARMA, or ARIMA, VAR is bi-directional. The bi-directionality means that each variable, or time series, is modelled as a function of its past values in VAR. In other words, the predictors are the lags of the series, with lags, of course, meaning time-delayed values. The VAR model allows for capturing the interactions and feedback effects among the variables, making it a powerful tool for analysing dynamic relationships in multivariate time series data.

Depicted as a formula, a general VAR model takes the following form:

$$\begin{bmatrix} Y_{1,t} \\ Y_{2,t} \\ Y_{3,t} \\ Y_{4,t} \\ \vdots \\ Y_{n,t} \end{bmatrix} = \alpha + \sum_{p=1}^{P} \beta_p * \begin{bmatrix} Y_{1,t-p} \\ Y_{2,t-p} \\ Y_{3,t-p} \\ Y_{4,t-p} \\ \vdots \\ Y_{n,t-p} \end{bmatrix} + \Theta * \begin{bmatrix} C_{exo,1} \\ C_{exo,2} \\ C_{exo,3} \\ C_{exo,4} \\ \vdots \\ C_{exo,n} \end{bmatrix} + \epsilon_t \tag{1}$$

With $Y_{n,t}$ being the estimated value for vector Y_n at moment t, α being the constant intercept for Y, β_p being the interaction coefficient between two Y_n's at lag p, $Y_{n,t-p}$ being the corresponding lagged value of Y_n, Θ being the coefficient for the exogenous control variables and e_t being the error term of Y at moment t. When incorporating the vectors used in the paper in the model, the formula changes to:

$$\begin{bmatrix} Ice_t \\ Hyb_t \\ EV_t \\ Elc_t \\ Gas_t \\ Gdp_t \\ Infr_t \\ Typ_t \\ CPI_t \end{bmatrix} = \alpha + \sum_{p=1}^{P} \beta_p * \begin{bmatrix} Ice_{t-p} \\ Hyb_{t-p} \\ EV_{t-p} \\ Elc_{t-p} \\ Gas_{t-p} \\ Gdp_{t-p} \\ Infr_{t-p} \\ Typ_{t-p} \\ CPI_{t-p} \end{bmatrix} + \Theta * \begin{bmatrix} Law_t \\ Subs_t \\ Int_t \end{bmatrix} + \epsilon_t \tag{2}$$

In the model, α depicts a $(9*1)$ vector of intercepts, β_p a $(9*9)$ matrix of coefficients for the variables at time $t-p$, Θ a $(9*3)$ matrix for the coefficients of the exogenous controlling variables, and ϵ_t a $(9*1)$ vector of error terms at time t. On the left, the estimated values of all six main vectors plus the three controlling endogenous variables, at time t are depicted. The controlling variables are all shown next to the Θ, whilst ϵ describes the error term.

Choosing a good value for p is crucial for the model, as an inappropriate selection lowers the accuracy of the outcomes. There are multiple criteria to help determine the optimal value of p, three of which are used in this paper. These are:

- Akaïke Information Criteria (AIC):

  The AIC balances the goodness of fit of a model and its simplicity by penalising additional variables and favouring lower AIC values.

- Hannan-Quinn Information Criterion (HQ):

  HQ selects an optimal model by balancing likelihood against a penalty for complexity, applying a milder penalty than the Schwarz Criterion, and is particularly effective in larger samples.

- Schwarz Criterion (SC):

  SC heavily penalises a model's complexity to avoid overfitting, favouring simpler models. It does so particularly in scenarios with limited data.

A mixture of criteria is used to ensure the most favourable p is chosen and that no curious coincidence makes a certain p the most excellent fit for just one of the criteria. Not selecting the optimal p would cause worse performance by the model, which is to be avoided. The model uses the p chosen by the most sets of criteria. The p that the AIC chooses is used if no two criteria choose the same one. Since AIC is the most widely used criterion, it is appropriate to be the primary selector. The maximum lags considered when determining the optimal p is 12. The annual swings are captured via a lag of 12, which improves the model's predictions.

5.2 Stationarity test

Stationarity is an important assumption in time series analysis, such as VAR models. Variables are stationary if their statistical characteristics, such as their variance or mean, remain constant over time. Using time series differences improves stationarity by eliminating trends and other non-stationary elements. Differencing transforms the data into a format where the statistical characteristics are constant across time, making it easier to use statistical models that require stationarity. The Augmented Dickey-Fuller (ADF) test is the most used statistical test in time series analysis to test for stationarity. The ADF test checks for a unit root in the data, the presence of which indicates non-stationarity. The test provides a t-statistic that is compared to critical values in order to draw a conclusion about the stationarity of the series. A rejection of the null hypothesis implies that the time series is stationary, allowing for use in VAR models. Initially, the absolute values of all variables are ADF tested. The non-stationary ones are differenced before being ADF tested again.

5.3 Granger causality

The Granger causality test is used to test if one time series contains information that helps predict another time series. To illustrate, the registrations for hybrids (HYB) and EVs (EV) are used. If HYB contains information that helps predict EV, then HYB Granger causes EV. To test for Granger causality, two VAR models are made. The first model only uses past values of EV for the future prediction of EV. The second model uses both past values of HYB and EV for its prediction of EV. Afterwards, the accuracies of these two models are compared. If it turns out that using past values of both HYB and EV significantly better predicts values of EV than only using past values of EV itself, this means that HYB does indeed Granger cause EV. Also here the number of lags p is an important factor and thus should be considered carefully. Please note that Granger causality does not imply an actual causal relationship. The test only implies a predictive relationship between the variables.

5.4 Impulse response analysis

The output of VAR models is extensive and thus complicated to show. Impulses response analyses (IRA) are used to allow easy interpretation and visualisation still. IRAs are a commonly used tool to estimate the effect of a certain shock on other variables over a period of time. For example, it estimates how HYB would react to a singular shock in EV and makes predictions of HYB for the next p months. Visualising the response over the next p months allows for a more straightforward interpretation. The responses in this plot display the change in registrations, not the registration level itself. If the initial reaction of HYB to a shock in EV is 500, the predicted value for HYB is 500 higher than when the shock would not have happened. It is not the case that the predicted value for HYB is 500. Because the responses are calculated for p months, they show both immediate and long-term reactions to the shock. By analysing the sign, significance and duration of the response, a clear picture can be painted about the relationship between the variables tested. For the robustness of the findings, bootstrapping is applied 100 times. This ensures the results are not based on luck by resampling the data used 100 times, which allows for providing useful confidence intervals. This is especially useful when using a larger dataset as used in this analysis.

6 Results

The results are discussed in five separate sections, with three more subsections. The first section analyses the correlation matrix between the six main vectors and all other variables in the model. The following section checks these main vectors for stationarity using the discussed ADF test. This is followed by determining the optimal p, after which the Granger causalities are examined. Finally, the impulse response analyses are discussed. This is done in three subsections: one for the dataset as a whole, one for the luxury moderators and one for the ownership moderator.

6.1 Correlation Matrix

The data reveals intriguing relationships between different vehicle types and economic indicators, each pair connected by correlation coefficients as shown in table 7.

Table 5: Correlation Table

	EV	**ICE**	**HYB**	**GDP**	**ELC**	**GAS**	**CHG**	**TYP**	**BPM**	**MRB**	**SEPP**	**INT**	**CPI**
EV													
ICE	-0.47												
HYB	0.42	-0.44											
GDP	0.20	-0.20	0.14										
ELC	0.28	-0.09	0.09	0.20									
GAS	-0.03	0.04	0.07	0.04	-0.23								
CHG	0.61	-0.61	0.73	0.06	0.08	0.03							
VAN	-0.06	0.57	-0.07	-0.16	-0.05	0.13	0.08						
BPM	0.35	-0.44	0.47	0.05	0.00	-0.05	0.61	0.05					
MRB	0.56	-0.42	0.46	0.04	0.05	0.04	0.81	0.22	0.59				
SEPP	0.59	-0.57	0.74	0.15	0.14	0.09	0.83	-0.02	0.33	0.55			
INT	0.18	-0.08	0.22	0.11	0.02	-0.01	0.24	0.06	0.11	0.15	0.22		
CPI	0.11	-0.16	0.14	-0.32	-0.13	0.04	0.25	0.01	0.07	0.15	0.23	0.18	

Notes: The table shows all correlation coefficients for each pair of vectors and or control variables.

The highest correlations are found when looking at the number of charging poles (ELC). It is found to have strong correlations with each of the three fuel types (EV(0.61), ICE(-0.61) and HYB(0.73)) and all three government policies (BPM(0.61), MRB(0.81) and SEPP(0.83)). This suggests that the number of charging stations is positively associated with EV and hybrid registrations whilst negatively associated with ICE registrations. Furthermore, this number is potentially influenced by the government's policies. Of these policies, the subsidy on EVs (SEPP) has the highest correlation with the fuel type registrations, higher than that of the other two discounts. Between the fuel type registrations themselves, moderate correlations are found. Both the EV (-0.47) and hybrid (-0.44) registrations are negatively correlated with ICE, whilst they are positively correlated (0.42). These coefficients may indicate an equal shift from ICE vehicles towards EVs and hybrids, whilst they only support each other's growth. Additionally, the small correlation found between GDP and all types of registrations suggests broader economic growth does not play a major role in determining vehicle registrations. On a final note, it's important to note that while correlations offer a glimpse into how variables relate, they don't confirm direct cause and effect. More statistical analyses are required to pinpoint the main factors influencing registrations.

6.2 Stationarity test

The first step in furthering the analysis is the Augmented Dickey-Fuller(ADF) test. This test is applied to the six principal vectors: hybrid vehicle registrations (HYB), EV registrations, ICE registrations, GDP, and prices for electricity (ELC) and gas (GAS). Initially, no differencing was applied to these vectors; they were put into the ADF test in their raw form. The outcomes are shown in Table 5.

Table 6: Non-differenced ADF

Variable	*T-statistic*	*Interpretation*
$Total\_EV$	-6.70	Stationary
$Total\_ICE$	-3.16	Stationary
$Total\_HYB$	-3.72	Stationary
GDP	0.64	Non-Stationary
ELC	-0.39	Non-Stationary
GAS	0.63	Non-Stationary

Table 7: Differenced ADF

Variable	*T-statistic*	*Interpretation*
$Total\_EV$	-6.65	Stationary
$Total\_ICE$	-2.90	Stationary
$Total\_HYB$	-3.69	Stationary
GDP	-8.93	Stationary
ELC	-3.04	Stationary
GAS	-11.69	Stationary

Notes: The tables show the t-statistic and interpretation for each of the main vectors, on the left before differencing, on the right after differencing.

As can be seen, all vehicle registration variables are stationary, as their relative t-statistics are -6.70 for EV registrations, -3.16 for ICE registrations and -3.72 for hybrid registrations. This suggests there to be no unit roots in the vectors, which makes them well-suited for direct inclusion in the VAR model without the need for differencing. On the other hand, the exogenous vectors of GDP and gas and electricity prices are established to be non-stationary, with the t-statistics lying between -0.39 and 0.64. To incorporate these variables into a VAR model, differencing them is needed. After this is done, the ADF tests are rerun.

As seen in table 6, all vectors are stationary after differencing the exogenous ones. The t-statistics for GDP (-8.93), electricity prices (-3.04) and gas prices (-11.69) now all indicate an absence of unit root in the vectors, making them fit for a VAR model. Note that the t-statistics for the vehicle registrations also have slightly changed. This is because the first three months of data had to be omitted to allow the differencing of the exogenous vectors. However, all vehicle registrations are still found to be stationary, which means all six principal vectors are now befitting for use in a VAR model.

6.3 Determining lags

Determining the correct number of lags is crucial for a VAR model. It tells the model how far back it should look for its predictions of the next value. As mentioned, multiple criteria are used to make a final decision. Also, remember that the maximum lag was determined to be 12. All the values for the different criteria are shown in table 10 in the appendix. To illustrate, figure 11 shows the AIC values for each lag.

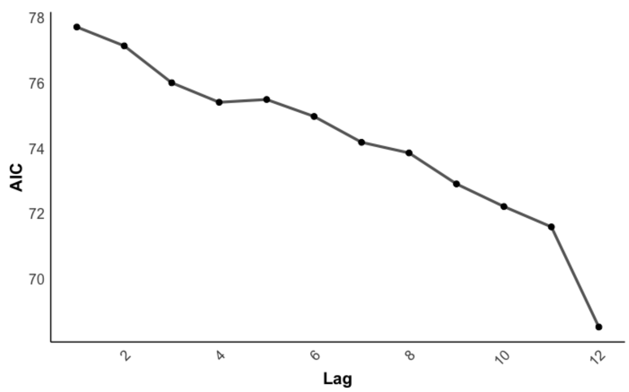


Figure 13: AIC scores for different lags

The figure clearly shows the optimal lag to be set to 12 months or one year. The AIC values tend to decrease with each lag, with the biggest drop seen from 11 lags to 12 lags. Note that the actual values for AIC do not need to be examined, as they do not tell much. Only the relative difference between the values is important. When looking at the other criteria, the HQ also estimates the optimal lag to be 12, whilst the SC estimates the optimal lag to be 1. As two of the three criteria, including the most often used AIC, select 12 as the optimal lag, this value of lags is used in further research.

6.4 Granger causality

The next stage in advancing the analytical efforts involves examining the Granger causal relationships among the primary vectors. The table below presents the F-test results from the Granger causality test for each combination of the primary vectors. The number of lags considered is set to 12, the optimal number of lags before.

Table 8: Granger causality

	Total_EV	***Total_ICE***	***Total_HYB***	***GDP***	***ELC***	***GAS***
Total_EV	-	0.73	0.53	2.37**	1.35	1.03
Total_ICE	1.05	-	1.37	2.58**	0.48	0.70
Total_HYB	1.90*	1.13	-	0.56	0.63	0.94
GDP	0.86	1.93*	0.51	-	0.55	1.89*
ELC	4.45***	0.26	0.41	2.12*	-	3.72***
GAS	1.43	0.30	0.80	1.09	4.09***	-

Notes: Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '^' 0.1 ' ' 1. Read table as row Granger causes column. The values represent the F statistics.

The highest and most significant coefficients are found when examining the electricity prices (ELC). The results indicate electricity prices to Granger cause EV registrations, GDP and gasoline prices, whilst being Granger caused by only gasoline prices. Because both electricity and gasoline prices Granger cause each other, it suggests the two variables to be connected dynamically. That the electricity prices Granger causes EV registrations emphasises the importance of electricity pricing dynamics in predicting future EV registrations. When examining the results between the fuel types, it is found that only hybrid registrations significantly Granger cause EV registrations. No other significant results are found between the fuel types. This indicates there to be little predictive power in past values of registration of other fuel types on the registrations for other fuel types. Hybrid registrations are not Granger caused by any other main vector, indicating the complexity of predicting future values. All in all, the Granger causality tests reveal many complex relationships between the main vectors. The impulse response analyses are examined next to understand the causal relationships in this web fully.

6.5 Impulse response analyses

Now onto the main results of the paper. As VAR models are too large to show and interpret in this paper, impulse response analyses are done to still allow for this. In total, 54 impulse responses have been generated. There are nine impulse responses analysed, each done six times. Once for the whole data set and five times for each group within the moderators. The nine impulses are between each pair of vehicle type registrations and between the three exogenous vectors and the hybrid registrations. The periods looked ahead are set at 12, the same number as the amount of lags used for the predictions. However, R also made predictions for the 13^{th} month after the shock, which will also be analysed.

6.5.1 All data

The first response analyses made are those using the complete set of data. The graphs below depict the reactions and the 90% confidence intervals for shocks in each type of fuel on both other types. The thick black lines depict the estimated change, and the grey area shows the confidence intervals. An estimated effect is deemed significant when the whole 90% confidence interval is below or above 0, or when the estimated effect (IRF) falls outside of the confidence interval.

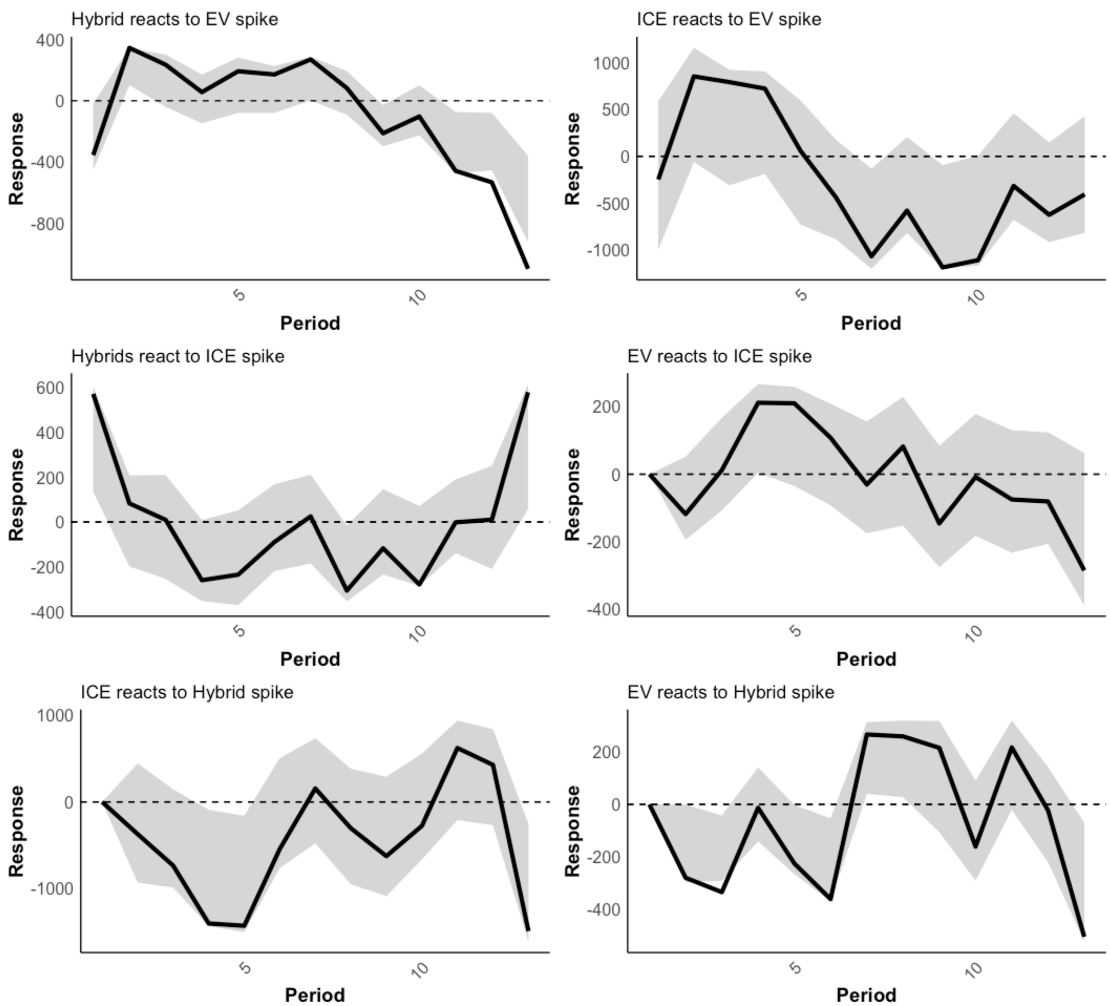


Figure 14: IRA of fuel types: all data

The first two graphs show that ICE and hybrid registrations react somewhat similarly to a spike in EV registrations. They both have a negative reaction before some recovery is seen in the next few months, after which the effects are negative again. The biggest difference in reaction between ICE and hybrids to an EV spike lies in the significance. Hybrid registrations show significantly negative responses at $t \in \{1, 9, 11 : 13\}$ and positive at $t \in \{2, 7\}$, whilst the ICE registrations only show a significant negative response at $t \in \{7, 9\}$ with no significant positive responses.

The reactions are less similar when looking at the responses of hybrids and EVs to an ICE registration spike. The hybrid registrations show an early significant positive response at $t = 1$, followed by a long period of negative responses, although only significant at $t = 8$. This is capped up by a final positive response at $t = 13$. The EV registrations show a completely different response. An initial insignificant negative response is followed by a significantly positive response at $t = 4$, after which a slow and insignificant downfall can be seen in the responses.

When comparing how ICE and EV registrations react to a spike in hybrid, the similarity found in the first two responses is seen again. Both show an initial negative response, followed by a recovery. Both responses show a small dip in this recovery before recovering further. Lastly, both again show a significantly negative response at $t = 13$. Apart from that, the responses differ quite a bit in significance. Where ICE only shows significantly negative responses at $t \in \{4, 5, 13\}$, EV also shows significant positive responses at $t \in \{7, 8\}$, besides negative significant responses at $t \in \{2, 3, 5, 6, 13\}$.

All in all, the findings indicate hybrids to be the most affected by spikes in other fuel-type vehicles whilst also causing the most significant responses. The negative responses of hybrids to an EV spike observed at both $t = 1$ and $t \in \{9, 11 : 13\}$ indicate that consumers may exhibit a delayed reaction to changes in the EV market, with the initial shock at $t = 1$ reflecting a quick response, followed by a gradual adjustment that culminates in a substantial long-term shift away from hybrid vehicles, potentially influenced by evolving preferences and market dynamics. This is, however, countered by both a significantly positive response of hybrids to a hybrid spike and a significant negative response when ICE reacts to a hybrid spike. This could indicate the cannibalisation of ICE by hybrids, which could offset the effect of the EV rise. The generally negative significant responses of EVs to a hybrid spike could indicate that EVs and hybrids are substitutes for each other. However, this cannot be said with extreme certainty based only on the IRA's. The next question is to see how the exogenous vectors affect the hybrid registrations.

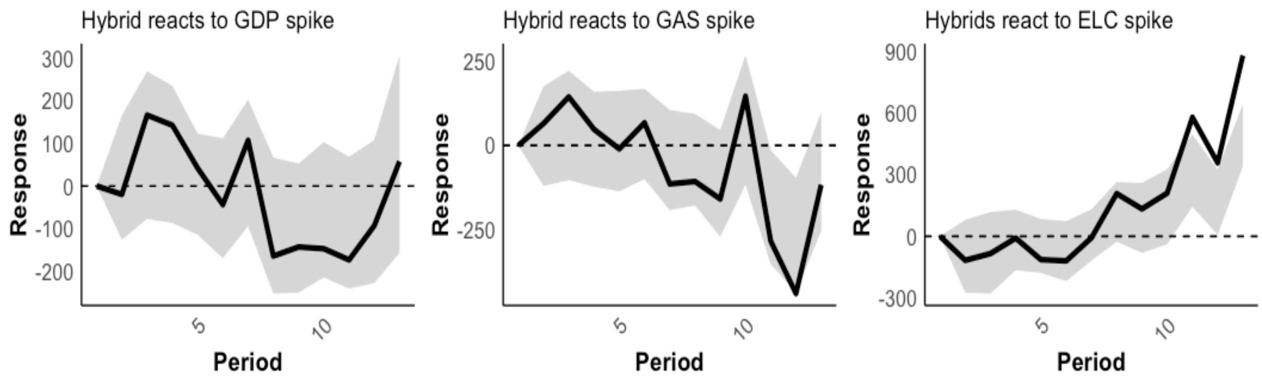


Figure 15: IRA of exogenous vectors: all data

A spike in GDP seems to have an initial positive effect on the hybrid registrations for the first seven months, followed by six months of negative responses. However, none of the reactions are significant. Gasoline prices are identified to cause a little response in hybrid registrations initially. However, after a slight delay, significant negative responses are found at $t \in \{11, 12\}$. Here, the complete confidence interval is negative, and the IRF is below the lower bound of the interval. This indicates a clear and strong statistical significance of a negative response to the shock. When looking at the effect of a spike in electricity prices, opposite responses are seen. After an initial delay, significantly positive responses are seen at $t \in \{11 : 13\}$.

These findings show that hybrid registrations are sensitive to economic factors like gas and electricity prices. When gas prices increase, hybrid registrations show a delayed, significantly negative response. This is possible because it is more attractive for consumers to go for an EV, given their independence from gas and consequent cost savings, ceteris paribus. Conversely, a significantly positive response in hybrid registrations is found when the price of electricity peaks. This effect is explained oppositely to the effect of gasoline prices. Now, hybrids become relatively cheaper to drive than EVs, ceteris paribus, making the hybrid vehicle more attractive for climate-aware consumers, thus raising hybrid registrations. These findings strengthen the possibility that hybrids and EVs are substitutes. Interestingly, the results suggest that a spike in GDP does not significantly affect hybrid registrations. While a strong economy can indicate greater consumer spending power, which could benefit the more expensive hybrids and EVs, it does not necessarily lead to a turn towards hybrid vehicles. Hence, unless GDP growth directly affects factors like fuel prices for eco-friendly vehicles, it may not directly impact hybrid registrations.[1]

[1]Predictions are made using a simplified version of the model. This simplified model only looks at the data yearly and only considers the six main vectors. The results are found in figure 20 in the appendix.

6.5.2 Luxury versus Non-luxury

Next up is to research whether there is a difference in reaction to the different spikes from the market's supply side. The figure below shows the same spikes and responses as researched before, but now the data has been split between luxury and non-luxury brands. The blue lines and area depict the response and 90% confidence interval of luxury brands, while the red line and area do so for non-luxury brands.

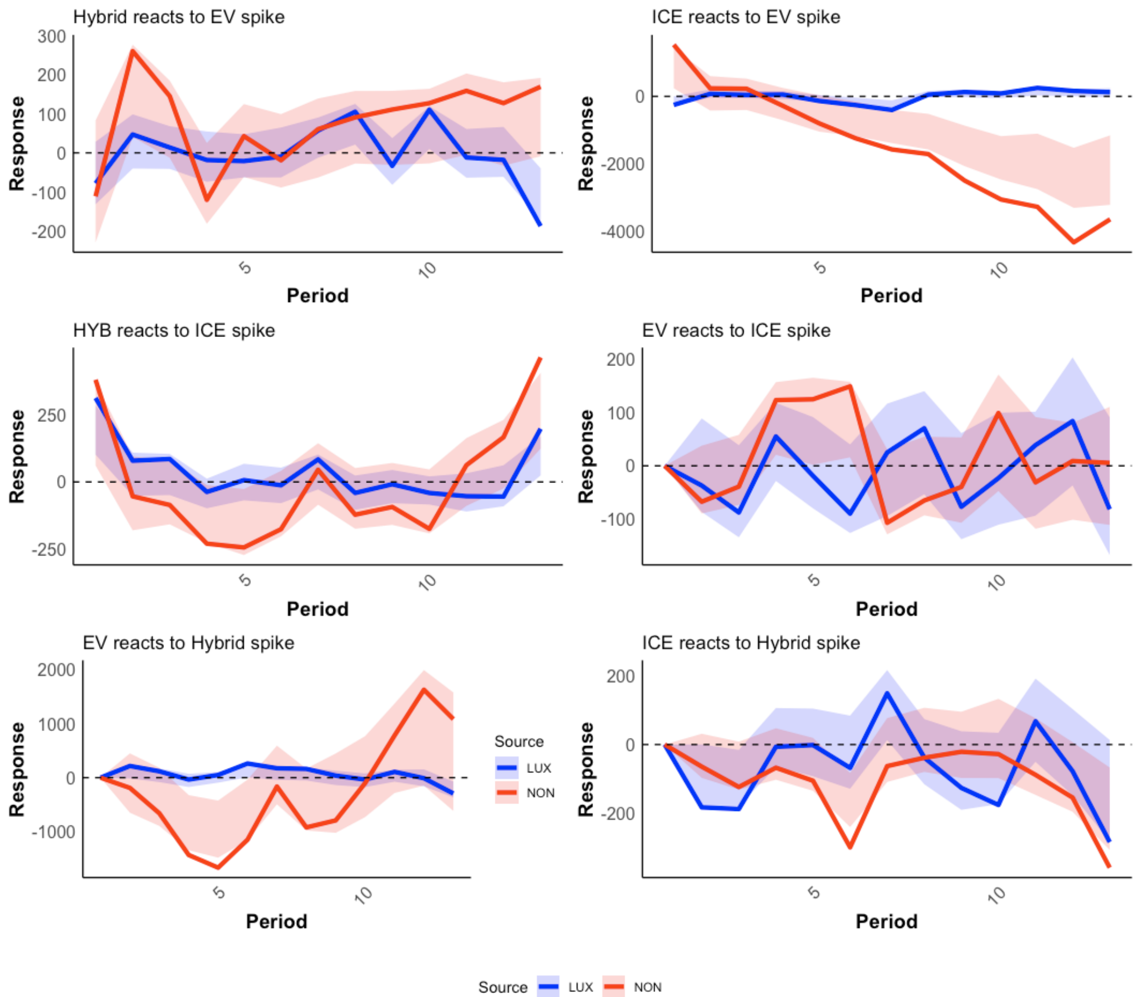


Figure 16: IRA of fuel types: luxury vs. non-luxury

As the overall effect of the spikes has already been discussed when considering the whole data set, the focus will now lie on the difference between the brand types. Diving deeper into the distinctions between luxury and non-luxury brands reveals an intriguing disparity in shocks to fuel type registrations. Big differences in responses are seen when examining the effects of an EV shock on hybrids and EV registrations. The hybrids show an initial similar response to the EV shock. A preliminary positive, albeit only significant for non-luxury at $t = 2$, is followed by a small decline in response before a gradual rise again. This gradual rise is significant for luxury brands at $t \in \{8, 10\}$, but insignificant for their counterpart. The big difference lies at $t = 13$. Here, non-luxury brands continue with insignificant positive reactions, while luxury hybrids see a strongly significant negative response. The differences between luxury and non-luxury are less when examining the effect of a shock in ICE registrations. The main difference here is the significant positive response of non-luxury EVs to the ICE spike at $t \in \{4 : 6\}$, whereas luxury EVs fail to produce any significant response. Similarly, when studying the responses of ICE to a hybrid spike, the line follows a comparable path, apart from the significance. Luxury generates significant negative responses at $t \in \{3, 10, 13\}$ and a positive one at $t = 7$, whilst non-luxury only responds significantly negatively at $t \in 6, 13$. The variation in response is even larger when seeing the responses of EVs to a hybrid spike. The non-luxury brands show significant responses at $t \in \{4 : 6\}$, with especially $t = 6$ being remarkable. This is because the luxury brands produce their only significant positive response at that t, alongside a significantly negative response at $t = 13$.

The difference in responses could be explained by the customers' demand elasticity, which might differ per type of brand. Luxury brands exhibit a less extreme response to shocks, indicating inelastic demand. This is most obvious when looking at how ICE registrations react to shocks in the newer technologies of hybrid and EV. The ICE registrations hardly show any significant changes, and the ones found are primarily positive. This indicates that the customers of the luxury brands stick to their purchase behaviour. Conversely, non-luxury brands tend to navigate a landscape of elastic demand, where consumers, often more price-sensitive, are open to adjusting their purchasing behaviours in response to the market. This can also be seen in the fact that there is a higher number of significant changes in the non-luxury responses compared to those of the luxury brands. All significant responses can be seen in table 12 in the appendix.

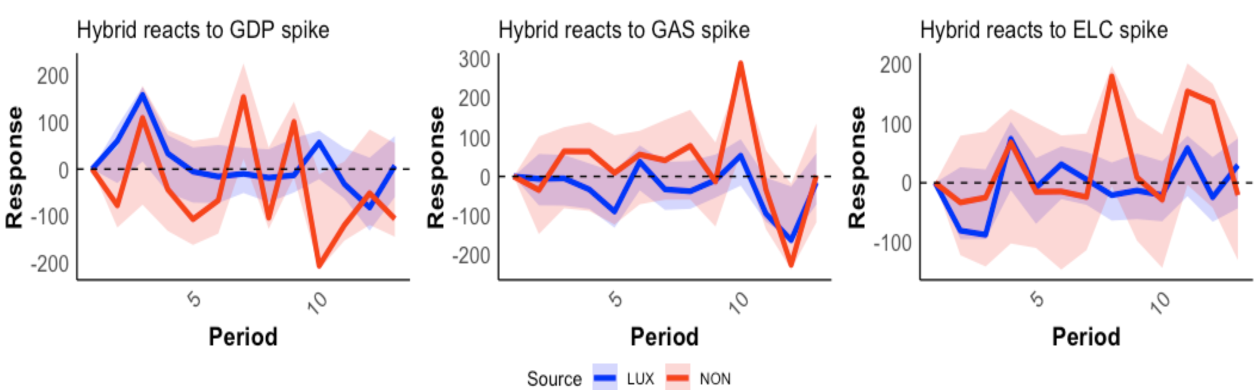


Figure 17: IRA of exogenous vectors: luxury vs. non-luxury

Studying the effect of shocks in the exogenous vectors sees the findings being dissimilar to those seen when considering the data set as a whole. Whereas the electricity prices were revealed to have the most overall effect, differentiating on the different comfort levels eliminates this significance. Moreover, a spike in GDP has a significant positive effect on both brand types, albeit at different t's, whilst in the overall picture, GDP was not found to have any significant effect. The only similarity in findings is seen when looking at the effect of a spike in gas prices. For both luxury and non-luxury brands, a delayed, significantly negative response is established on hybrid registrations. At $t = 12$, both moderators see a decrease in hybrid registrations when gas prices spike.

The different consumption patterns could explain why neither brand type seems to react to electricity prices in their hybrid registrations. Whereas the affluent customers of luxury brands do not care about the electricity prices, as they can afford it anyway, the, generally speaking, less wealthy purchasers of non-luxury brands are only strengthened in their choice for the already cheaper alternative of ICE. The significant positive influence of GDP spikes at differing time points for both brand types can also be explained through the difference in prosperity between the customers. The affluent clientele of luxury brands does not necessarily need the extra money coming with the higher GDP and are therefore quicker ($t = 3$) in spending the extra money on a more expensive vehicle like a hybrid. For non-luxury consumers, there might be more urgent destinations for the money than buying a newer, more expensive car. This explains why only at a later time ($t = 7$), after these consumers paid for other more compelling things and had time to save up, a significant increase is found in the registrations of hybrids. The economic reasoning behind the delayed negative response of hybrid registrations to a gas price spike is similar to that discussed when considering the whole data set.

6.5.3 Ownership

The other moderators are used to look at the demand side of the market. The figure below shows the same spikes and responses as before, but now the data has been split up based on the type of owner. Blue represents the business, red represents the car industry itself, and green depicts the private registrations.

The figure exposes big differences in responses between the owners to spikes of different fuel-type vehicles. There is no single spike to which the different owners all react the same. Private and the industry show a somewhat similar reaction in hybrid registrations, as both only show positive significant responses. For the industry this is at $t \in \{9, 10, 12\}$, for private at $t \in \{1, 2, 11\}$. On the other hand, the reaction of private begins with a significant negative response at $t = 1$, followed

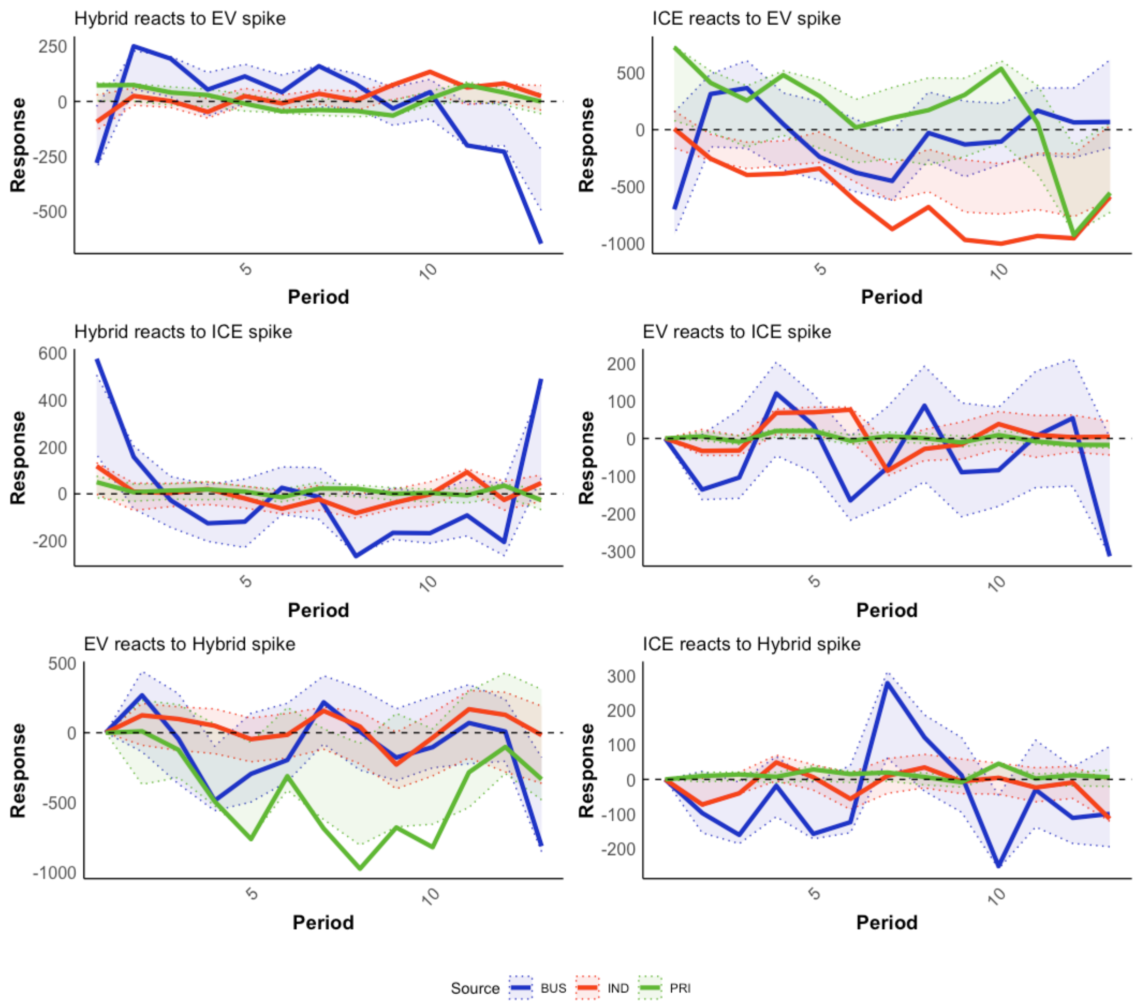


Figure 18: IRA of fuel types: types of ownership

by a significant positive response at $t \in \{2, 3\}$, and ending with a strongly significant negative response at $t \in \{11 : 13\}$. The ICE responses are just as dissimilar. The businesses show only a negative significant response at $t = 7$, whilst private first reacts significantly positively ($t = 1$), but ends with a strongly significant negative response ($t = 12$). Meanwhile, the industry shows a delayed, strongly significant negative response from $t = 2$ to $t = 13$. Moreover, the business hybrids registration shows a strongly significant positive response at both the beginning and the end ($t \in \{1, 13\}$), with a significant negative response at $t \in \{8, 10\}$ in between. The industry has a significant positive response at $t = 11$ and a negative one at $t = 8$, while private is not significantly influenced. Also, in the EV reaction to a hybrid spike, major variation is found between the types of owners. The industry shows no significant response, the businesses show a negative significant response at $t \in \{4, 13\}$, but private shows a significant negative response at nearly the whole second half of the year ($t \in \{5, 7, 8, 9, 10\}$). Also in the final IRA between fuel types, sizeable differences are found in significance. The industry shows only a significant negative response at $t = 13$, whereas private only shows a positive significant response at $t = 10$. The businesses, in contrast, show both significant negatives, at $t \in \{3, 5, 10\}$, and significant positive responses, at $t = 7$. When comparing the individual responses to the overall response, the business responses clearly emulate them most.

A difference in responses can be expected, as the different ownership types have different considerations when procuring a new car. Private owners only have to think about what they want, while the businesses and the industry must also consider public perception. Even between businesses and the industry, the considerations are different. For example, car rental companies, which fall under the industry label, have to think about what their customers want, as they have to use their services, and good market positioning is crucial for any company. On the other hand, when looking at a building company, for example, only company employees will likely use the car. Therefore, practicality is the most crucial factor for them. Government policies also provide a potential source of differentiation. For example, businesses cannot apply for the subsidy on EVs, which only affects private. On the other hand, companies do not need to pay any BPM, disregarding the fuel type, whereas private has to pay this and only get a discount on EVs.

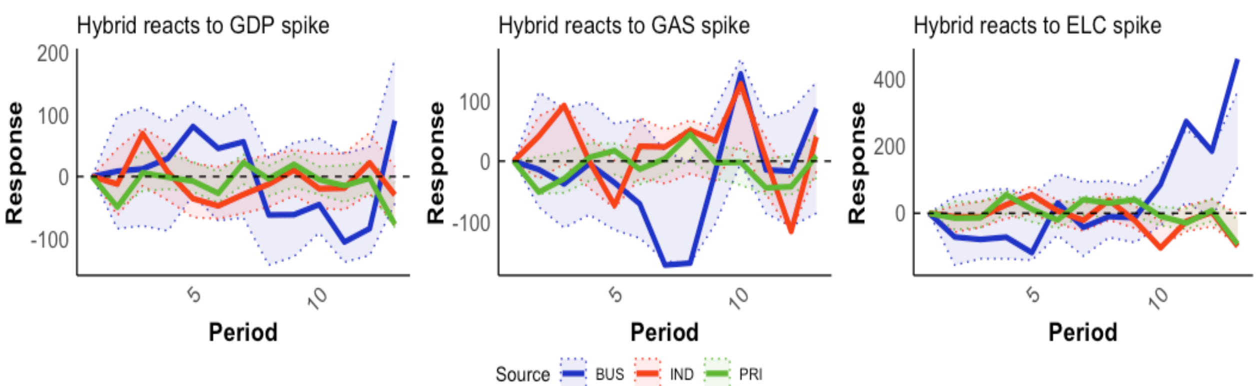


Figure 19: IRA of exogenous vectors: types of ownership

While examining the responses to spikes in the various exogenous vectors, the dissimilarities continue. A GDP spike does not impact both the industry and the businesses in hybrid registrations, whilst private sees a significantly negative response at $t = 13$. If there is a spike in gas prices, much more significance is seen. The businesses react negatively at $t \in \{7, 8\}$, whilst private reacts positively at $t = 8$. The industry shows a mixed reaction, with $t = 10$ being positive and $t = 12$ negative. A spike in electricity prices sees private and industry react similarly, showing significant negative responses at $t = 13$ and $t = 10$ for the industry. The businesses, however, show positive responses, both at $t = 11$ and $t = 13$.

The negative response of private to a spike in GDP can be declared through the possibility that consumers might go for the even more expensive EV if there is a higher GDP, as there is more money to spend. The positive reaction of the industry and private to a spike in gas prices can be explained by the fact that hybrids simply use less gas compared to traditional ICE. Finally, the adverse reaction of the industry and private to a spike in electricity could be because of similar reasons, as explained when discussing the findings from the complete data. For businesses, the spike might have even the most climate-aware companies staying away from completely electric vehicles due to the high costs. But since they still want a green image, they go for a less electricity-dependent vehicle like the hybrid. This leads to more hybrids registered, which is shown by the significant positive response.

7 Conclusion

The automobile market has seen a significant transformation in recent times. This paper attempted to find out how the biggest change, the introduction of electric vehicles, has impacted hybrid registrations. This is done in a world-leading country regarding the transition from traditional internal combustion engines and hybrids to electric vehicles in the Netherlands. The researched time frame is from January 2007 to December 2022. A vector autoregressive model is used to examine the effect of the rise of electric vehicles on hybrid registrations. This model contained six total vectors, three endogenous and three exogenous vectors. The endogenous vectors are compiled of the registration of hybrids, the registrations of internal combustion engine vehicles and the registrations of electric vehicles, while the exogenous vectors used are the gross domestic product, the gasoline prices and the electricity prices. The last two vectors are used as they account for the fuel used by the different types of vehicles. The other vectors need no elaboration. In total, there were six models made. The main configuration contained all data, the next two versions split the data into luxury and non-luxury brands, and the final three models split the data based on the type of owners. The three options for this were private owners, businesses and the vehicle industry itself. After the descriptives were made, the variables were ensured to be stationary, and the optimal lag was found to be 12 months. The vector autoregressive models were made, and the impulse analyses were done to allow for better interpretation.

The results show that hybrid registrations are significantly negatively affected by a rise in EV registrations, both in the short and long run. An initial negative response is followed by a gradual adjustment, which ends in a substantial long-term shift from hybrids to EVs. On the other hand, the hybrid registrations are also significantly positively affected by a spike in ICE registrations. First, not much response is seen, but again, eventually, a long-term shift is found, this time towards the registrations of hybrids. Besides, it is found that ICE reacts negatively to a spike in hybrid registrations, again both in the short and long term. When examining the effect of the exogenous vectors on the overall hybrid registrations, no significant effects are revealed when there is a spike in GDP. However, stocks in gasoline and electricity prices produce significant responses. For an electricity shock, a significant positive response is found after just under a year, while a gasoline spike response is delayed similarly but negative.

The models for the different moderators uncover some intriguing variation in responses. The greatest differentiation is identified when examining the effects of an EV shock on ICE registrations.

Here, the non-luxury brands show a slightly delayed but strongly negative response, whilst luxury brands show even a positive response as time passes. The variation in reaction can be explained through elasticity, as luxury brands are found to be relatively more inelastic compared to their non-luxury counterparts. Also, large distinctions are uncovered when looking at the different types of owners. There is no single spike to which the three types react the same. The industry's reactions stand out, with its strong reaction to EV shock and significant responses to nearly all other shocks. The business responses are found to be most similar to the overall response.

The findings corroborate with multiple papers cited in the literature review. For example, Nieuwenhuis and Wells (2003), states that diffusion is influenced by a range of economic factors, which this research confirms seeing the significant effect of shocks in the exogenous vectors. Also, the findings of Nisbet and Myers (2007) and Boykoff and Yulsman (2013) are supported by this paper, as also here, a clear trend towards climate-beneficial products is seen in the impulse response analyses. However, there are also multiple papers cited in the review whose findings are contradicted by this research. Where Baiardi and Morana (2021) find countries with higher to be more climate aware, here there is no significant effect found on the registrations by a shock in GDP. The same goes for Sun et al. (2021), who claim sustainability to be connected to luxury, and Vintró et al. (2014), who state businesses to be more aware of this. The findings in this research do not support either of these papers.

The findings do not suggest that hybrid registrations will quickly die off due to the rise in EV registrations. Although EV registrations are discovered to influence hybrid registrations in a negative sense significantly, this is countered by a significant effect of hybrid registrations on ICE registrations. These ICE registrations are, however, negatively affected by the rise of EVs and by a shock in hybrid registrations, with nothing to counter this loss. The results also show that the exogenous vectors influence the hybrid registrations, although no vector is found to produce the same responses across all different models. All in all, it is found that hybrid cars are not yet running out of Dutch road, despite the rise in EVs.

8 Limitations and future research

While this paper contributes to the existing literature and is grounded in a robust conceptual framework and methodology, it does have certain limitations, some of which may be addressed by future research. The most obvious is the absence of pricing information in the data. Adding pricing information to the data set could greatly improve the models. It would allow for distinction between individual car models instead of brands, which is not perfect because of its subjectivity. To illustrate this, some brands classified as luxurious might also have a less-luxurious model in their lineup, which is still classified as luxury because of the underlying brand. For example, there are multiple models of KIA which are more expensive and arguably more luxurious than the cheapest models of BMW or Mercedes. However, these KIA models would still be classified as non-luxury, while the BMW models are still considered luxurious. Another limitation arises from the other moderators, the ownership types. Although they are helpful in differentiating the demand side of the market, they might oversimplify it a bit. There is no differentiation between small and large companies, be it within the industry or other businesses, and no differentiation between urban and rural private buyers. All of these factors seem plausible to affect the results and, therefore, might need to be looked at by future research. The final limitation discussed again originates from the data, but this time concerns that only Dutch data is considered. The specific characteristics of the Dutch consumer might play a significant role in the transition to EVs, which prevents the results of this paper from being generalised to other cultures and countries.

Besides the aforementioned limitations, more points should be addressed by future research. Future research could focus on differentiation within fuel types. For example, looking at the effect of the EV introduction on different car segments might be interesting, or there might be a different response between plug-in and classical hybrids. Moreover, future research could focus on considering the technological advancements of EVs. Since their introduction, they have seen a major increase in range and a similar decrease in price, which is feasible to affect registrations. In short, further research is needed to grow the general understanding of the transition to EV. The hope is that this paper sparks the interest to examine the intricate market of cars and see how much road there is left for the hybrid versions.

Appendix

Table 9: Money payed by SEPP

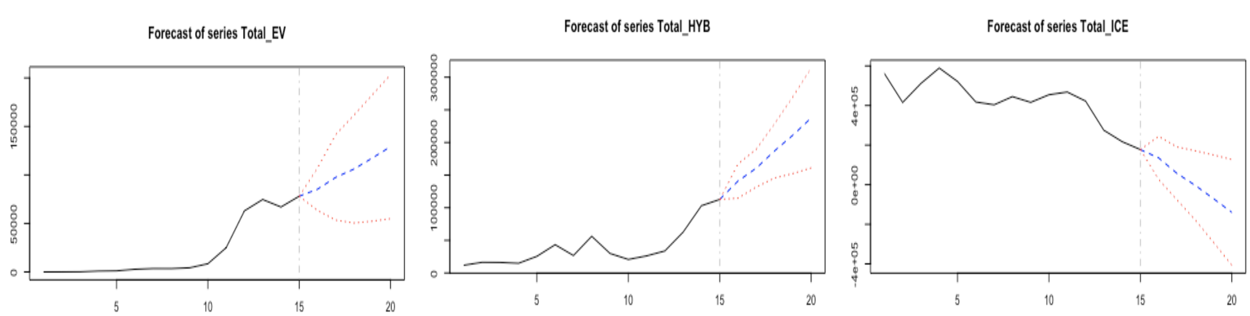
	New cars			Second hand		
Year	***Bugdet***	***Subsidy***	***Cars***	***Bugdet***	***Subsidy***	***Cars***
2020	€10m.	€4000	2500	€7.2 m.	€2000	3600
2021	€14.4m.	€4000	3600	€13.5 m.	€2000	6750
2022	€71m.	€3350	21194	€20.4 m.	€2000	10200
2023	€67m.	€2950	22711	€32.4 m.	€2000	16200
2024	€58m.	€2550	22745	€29.4 m.	€2000	14700

Notes: The table shows the money in the total money pot of SEPP per year, the subsidy per car and the total number of cars for both new and second-hand cars.

Table 10: Criteria Values for Different Lags

Lag	***AIC(n)***	***HQ(n)***	***SC(n)***
1	80.38	81.04	**82.00**
2	79.83	81.08	82.90
3	78.51	80.34	83.03
4	77.98	80.41	83.96
5	77.90	80.91	85.33
6	77.46	81.06	86.34
7	76.84	81.03	87.18
8	76.86	81.64	88.64
9	75.85	81.22	89.09
10	75.16	81.12	89.86
11	74.35	80.89	90.49
12	**71.02**	**78.16**	88.62

*Notes:*The table shows all criteria values for the AIC, HQ, SC and FPE. The maximum lag was set at 24. The bold values indicate the best lag values according to that criterion.



EV **HYB** **ICE**

Figure 20: Second attempt at forecasting

Table 11: Distribution between moderators

Brand	*Registrations*	*Rank*	*Luxury*	*Non-Luxury*	*Source*
Aiways	467	59	×		Own
Alfa Romeo	31716	27	×		KBB
Alpine	189	65	×		Own
Aston Martin	456	60	×		Own
Audi	255868	14	×		KBB
Bentley	856	51	×		Own
BMW	284793	10	×		KBB
BYD	644	55		×	Own
Cadillac	592	56	×		KBB
Chevrolet	48647	25		×	KBB
Chrysler	5627	43		×	KBB
Citroën	343205	9		×	Own
Cupra	4509	46		×	Own
Dacia	68013	23		×	Own
Daihatsu	25044	30		×	Own
Daimler	19	80	×		Own
Dodge	10585	38		×	KBB
DS	6598	42	×		Own
Ferrari	644	54	×		Own
Fiat	275760	12		×	KBB
Fisker	189	64	×		Own
Ford	594012	4		×	KBB
Fuso	1177	50		×	Own
Goupil	506	58		×	Own
Honda	53725	24		×	KBB
Hongqi	32	74	×		Own
Hummer	80	72	×		Own
Hyundai	258269	13		×	KBB
Infiniti	669	53	×		KBB
Isuzu	1462	48		×	Own
Iveco	26373	28		×	Own
JAC	27	77	×		Own
Jaguar	14201	33	×		KBB
Jeep	12336	36		×	KBB
Kia	351085	8		×	KBB
Lada	155	66		×	Own
Lada-Vaz	19	79		×	Own
Lamborghini	244	63	×		Own
Lancia	5591	44	×		Own
Land Rover	25784	29	×		KBB
Landwind	58	73		×	Own
LDV	367	61		×	Own
Lexus	21656	31	×		KBB
Lotus	94	71	×		Own
Lucid	17	81	×		KBB
Lynk & Co	12740	35	×		Own
Man	5209	45		×	Own
Maserati	800	52	×		KBB
Maxus	519	57		×	Own
Maybach	6	83	×		Own
Mazda	116468	19		×	KBB
McLaren	101	68	×		Own
Mercedes	368382	7	×		KBB
MG	6838	40		×	Own
Micro-Vett	27	76		×	Own
Mini	77453	21		×	KBB
Mitsubishi	113034	20		×	KBB
Mitsubishi Fuso	13	82		×	Own
Morgan	99	70	×		Own
Nio	100	69	×		Own
Nissan	189499	16		×	KBB
Opel	585689	5		×	Own
Others	41111	26			
Peugeot	632780	3		×	Own
Polestar	8184	39	×	×	KBB
Porsche	20574	32	×		KBB
Quattro	300	62	×		Own
Renault	647186	2		×	Own
Rolls-Royce	147	67	×		Own
Rover	28	75	×		Own
Saab	6733	41	×		Own
Seat	170968	18		×	Own
Skoda	254193	15		×	Own
Smart	12980	34		×	Own
Ssangyong	1650	47	×		Own
Subaru	11909	37		×	KBB
Suzuki	173798	17		×	Own
Tesla	72619	22	×		KBB
Toyota	494568	6		×	KBB
Van Blitterswijk	1363	49		×	Own
Volkswagen	1002038	1		×	KBB
Volvo	281154	11	×		KBB
Xpeng	20	78	×		Own

Notes: The table shows for each of the brands whether they are considered luxury or non-luxury, alongside the source for this, the total registrations and the ranking of registrations. KBB stands for Kelley Blue Books.

Table 12: **Significant t's from Impulse Response Analyses**

Data	Sign	1	2	3	4	5	6	7	8	9
ALL	*Pos*	2,7		1,13	4		7,8			11:13
	Neg	1,9,11:13	7,9	8		4,5,13	2,3,5,6,13		11,12	
LUX	*Pos*	8,10	11,12			6	7	3		
	Neg	13	6,7	1,13		13	3		11,12	
NON	*Pos*	2	1	1,13	4:6			7	10	
	Neg		6:13	4,5		4:6	6,13	10	12	
BUS	*Pos*	2,3		1,13			7			11,13
	Neg	1,11:13	7	8,10	13	4,13	3,5,10		7,8	
IND	*Pos*	9,10,12		11	4,5 7				10	
	Neg		2:12	8	7		13		12	10,13
PRI	*Pos*	1,2,11	1		4,5		10		8	
	Neg		12			5,7:10		13		13

Notes: The table shows for which t a significant response was found. The responses are split on moderators, and between positive (Pos) and negative (Neg).

References

ACEA (2022). Electric cars: Half of all chargers in eu concentrated in just two countries. https://www.acea.auto/press-release/electric-cars-half-of-all-chargers-in-eu-concentrated-in-just-two-countries/: :text=Brussels

ACEA (2023). Fuel types of new cars. https://www.acea.auto/fuel-pc/fuel-types-of-new-cars-battery-electric-12-1-hybrid-22-6-and-petrol-36-4-market-share-full-year-2022/.

Akerlof, G. A. and Kranton, R. E. (2000). Economics and identity. *The quarterly journal of economics*, 115(3):715–753.

Algemeen Dagblad (2023). Definitief verbod op verkoop nieuwe benzine- en dieselauto's vanaf 2035. https://www.ad.nl/auto/definitief-verbod-op-verkoop-nieuwe-benzine-en-dieselautos-vanaf-2035 ada60b36/.

Aliyev, F., Wagner, R., and Seuring, S. (2019). Common and contradictory motivations in buying intentions for green and luxury automobiles. *Sustainability*.

Anderson, H. (2011). Vars, cointegration and common cycle restrictions.

ANWB (2023a). Bpm: Belasting van personenauto's en motorfietsen. https://www.anwb.nl/auto/autobelastingen/bpm.

ANWB (2023b). Geen wegenbelasting voor elektrische auto's tot 2025. https://www.anwb.nl/auto/elektrisch-rijden/geen-wegenbelasting-voor-elektrische-autos.

Athlon (2023). Aantal laadpalen in nederland stijgt naar 1.7 miljoen in 2030. https://www.athlon.com/nl/kennisbank/aantal-laadpalen-in-nederland-stijgt-naar-1-7-miljoen-in-2030/.

Autoblog (2022). Laatste echte lamborghini komt in 2022, daarna hybride. https://www.autoblog.nl/nieuws/laatste-echte-lamborghini-komt-in-2022-daarna-klaar-3413980.

Autoverleden.nl (2014). Auto verkoop cijfers per maand en jaar. https://www.autoverleden.nl/Auto-verkoop-cijfers-per-maand-en-jaar/: :text=Gemiddelde

Autovista (2023). Bevs lead the netherlands new-car market in august. https://autovista24.autovistagroup.com/news/bevs-lead-netherlands-new-car-market-august/.

Autoweek (2022). Nieuwe elektrische sedan van mercedes-benz. https://www.autoweek.nl/autonieuws/artikel/nieuwe-compacte-elektrische-sedan-van-mercedes-benz-betrapt/.

Autoweek (2023). Polestar noteert enorme verkoopgroei over 2022. https://www.autoweek.nl/autonieuws/artikel/polestar-noteert-enorme-verkoopgroei-over-2022/.

Awadallah, M. (2018). Comparative fuel economy, cost and emissions analysis of a novel mild hybrid and conventional vehicles. *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*.

Azarafshar, R. (2020). Electric vehicle incentive policies in canadian provinces. *Energy Economics*.

Back, W. (1995). Monte carlo simulation as tool for process reengineering. *Journal of Management in Engineering*.

Baiardi, D. and Morana, C. (2021). Climate change awareness: Empirical evidence for the european union. *Energy Economics*, 96:105163.

Bayus, B. L. (1994). Are product life cycles really getting shorter? *Journal of product innovation management*, 11(4):300–308.

Bayus, B. L. (1998). An analysis of product lifetimes in a technologically dynamic industry. *Management Science*, 44(6):763–775.

BloombergNEF (2022). Electric vehicle outlook 2022. *Bloomberg Finance L.P.*

BMW (2023). List of bmw models. https://www.bmw.nl/nl/modellen.html?tl=grp-wdpl-bcom-mix-mn-.-nscf-.-.-.

Borgstede, M. (2021). Quantitative and qualitative approaches to generalization and replication–a representationalist view. *Frontiers in Psychology*, 12.

Boykoff, M. T. and Yulsman, T. (2013). Political economy, media, and climate change: sinews of modern life. *Wiley Interdisciplinary Reviews: Climate Change*, 4(5):359–371.

Burke, P. J. (2012). Gasoline prices, gasoline consumption, and new-vehicle fuel economy: evidence for a large sample of countries. *Energy Economics*.

CarsDirect (2022). A brief history of hybrid cars. https://www.carsdirect.com/green-cars/a-brief-history-of-hybrid-cars.

CarsDirect (2023). Average ev transaction price exceeds $65.000. https://www.carsdirect.com/automotive-news/green-technology/average-ev-transaction-price-exceeds-65-000.

Chen, F., Ngniatedema, T., and Li, S. (2018). A cross-country comparison of green initiatives, green performance and financial performance. *Management Decision*, 56:1008–1032.

Clark, K. B., Fujimoto, T., et al. (1991). *Product development performance: Strategy, organization, and management in the world auto industry.* Harvard Business Press.

CNBC (2023). How inflation and higher interest rates have reshaped car buying. https://www.cnbc.com/2023/06/01/how-inflation-and-higher-interest-rates-changed-car-buying.html.

De Haan, P., Mueller, M. G., and Peters, A. (2006). Does the hybrid toyota prius lead to rebound effects? analysis of size and number of cars previously owned by swiss prius buyers. *Ecological Economics*, 58(3):592–605.

Dekker, P., Ridder, J. d., Houwelingen, P. v., and Miltenburg, E. (2020). *Burgerperspectieven 2020— 2.*

Dijk, M., Wells, P., and Kemp, R. (2016). Will the momentum of the electric car last? testing an hypothesis on disruptive innovation. *Technological Forecasting and Social Change*, 105:77–88.

Doyle, P. and Hooley, G. (1992). Strategic orientation and corporate performance. *International Journal of Research in Marketing*, 9:59–73.

ElaadNL (2011). Feestelijke opening 1000e oplaadpunt voor elektrische auto's. https://elaad.nl/feestelijke-opening-1000e-oplaadpunt-voor-elektrische-autos/: :text=Het

Fernandes, T. R. and Dantas, F. d. C. (2020). Effects of monetary policy transmission mechanism on car sales in brazil after the real plan. *Gestão & Produção*, 27.

Gadenne, D., Sharma, B., Kerr, D., and Smith, T. (2011). The influence of consumers' environmental beliefs and attitudes on energy saving behaviours. *Energy policy*, 39(12):7684–7694.

Gmelin, H. and Seuring, S. (2014). Achieving sustainable new product development by integrating product life-cycle management capabilities. *International Journal of Production Economics.*

Gmelin, H., Seuring, S., and et al. (2014). Determinants of a sustainable new product development. *Journal of Cleaner Production.*

Heine, K. and Phan, M. (2011). Trading-up mass-market goods to luxury products. *Australasian Marketing Journal*, 19:108 – 114.

Holweg, M. and Greenwood, A. (2001). Product variety, life cycles, and rate of innovation–trends in the uk automotive industry. *World Automotive Manufacturing*, 36:12–16.

IBISWorld (2023). Global car and automobile sales - market size. https://www.ibisworld.com/global/market-size/global-car-automobile-sales/.

Institute, W. R. (2023). These countries are adopting electric vehicles the fastest. https://www.wri.org/insights/countries-adopting-electric-vehicles-fastest: :text=The

Kaminski, J. (2011). Diffusion of innovation theory. *Canadian Journal of Nursing Informatics*, 6(2):1–6.

KBB (2023). Non-luxury report. https://www.coxautoinc.com/market-insights/q1-2023-kelley-blue-book-brand-watch-non-luxury-report/.

Kelley Blue Books (2021). What is a luxury car. http://www.kbb.com/what-is/luxury-car/.

Konstantakis, K. N., Milioti, C., and Michaelides, P. G. (2017). Modeling the dynamic response of automobile sales in troubled times: A real-time vector autoregressive analysis with causality testing for greece. *Transport Policy*, 59:75–81.

Lee, P.-C. (2010). Quantitative mapping of scientific research—the case of electrical conducting polymer nanocomposite. *Technological Forecasting and Social Change*, 78:132 – 151.

Lee, W.-S. (2018). Forecasting new product diffusion using both patent citation and web search traffic. *PLoS ONE*, 13.

Linhares, C. D. G. (2019). A scalable node ordering strategy based on community structure for enhanced temporal network visualization. *Comput. Graph.*, 84:185–198.

Ma, S. (2020). A deployment model of ev charging piles and its impact on ev promotion. *Energy Policy*.

MacDuffie, J. P., Sethuraman, K., and Fisher, M. L. (1996). Product variety and manufacturing performance: evidence from the international automotive assembly plant study. *Management Science*, 42(3):350–369.

Malancea, I. (2022). Competitive strategies for creating the company's image. *Economica*.

Nicholson, N. and Robertson, D. C. (1996). The ethical issue emphasis of companies: Content, patterning, and influences. *Human Relations*, 49:1367 – 1393.

Nieuwenhuis, P. and Wells, P. (2003). *The automotive industry and the environment*. Woodhead Publishing.

Nisbet, M. C. and Myers, T. (2007). The polls—trends: Twenty years of public opinion about global warming. *Public Opinion Quarterly*, 71(3):444–470.

Olivella-Rosell, P. (2014). Assessment of the impact of electric vehicles on iberian day-ahead electricity market. *2014 IEEE International Electric Vehicle Conference (IEVC)*.

Pantano, E., Passavanti, R., Priporas, C.-V., and Verteramo, S. (2018). To what extent luxury retailing can be smart? *Journal of Retailing and Consumer Services*.

Pauwels, K. H. (2017). Modern (multiple) time series models: The dynamic system. *Advanced methods for modeling markets*, pages 115–148.

Penna, C. C. and Geels, F. W. (2015). Climate change and the slow reorientation of the american car industry (1979–2012): An application and extension of the dialectic issue lifecycle (dilc) model. *Research Policy*, 44(5):1029–1048.

PureEnergie.nl (2023). Gemiddeld stroomverbuik per jaar. https://pure-energie.nl/kennisbank/gemiddeld-stroomverbruik-per-jaar/: :text=Bij

Qian, L. (2014). Using diffusion models to forecast market size in emerging markets with applications to the chinese car market. *Journal of Business Research*, 67:1226–1232.

Rogers, E. M. (2010). *Diffusion of innovations*. Simon and Schuster.

RTL Nieuws (2023). Ecb verhoogt rente voor de tiende keer op rij, tot hoogste punt ooit. https://www.rtlnieuws.nl/economie/beurs/artikel/5407627/ecb-verhoog-officiele-rente-lagarde.

RVO (2022). Subsidie regeling elektrische personenauto's particulieren (sepp). https://www.rvo.nl/subsidies-financiering/sepp.

Sarmento, J. (2016). The determinants of value added tax revenues in the european union. *Portuguese Journal of management Studies*.

Sinkinson, M. (2015). Ask your doctor? direct-to-consumer advertising of pharmaceuticals. *NBER Working Paper Series*.

Soltani-Sobh, A. (2017). Analysis of the electric vehicles adoption over the united states. *Transportation research procedia*.

Stark, J. (2022). Product lifecycle management (plm). In *Product Lifecycle Management (Volume 1) 21st Century Paradigm for Product Realisation*, pages 1–32. Springer.

Statista.com (2022). Most important factors when buying a car. https://www.statista.com/chart/13075/most-important-factors-when-buying-a-car/.

Statzon (2023). Half million ev charging points in the european union but more is needed. https://statzon.com/insights/ev-charging-points-europe: :text=The

Sun, J. J., Bellezza, S., and Paharia, N. (2021). Buy less, buy luxury: Understanding and overcoming product durability neglect for sustainable consumption. *Journal of Marketing*, 85:28 – 43.

Tarei, P. K. (2021). Barriers to the adoption of electric vehicles: Evidence from india. *Journal of Cleaner Production*.

Tesla (2023). Tesla global website. https://www.tesla.com.

The Wall Street Journal (2023). The world economic forum is coming for your cars. https://www.wsj.com/articles/world-economic-forum-paper-reduce-cars-by-2050-davos-private-jets-climate-f0bb64b9.

Times, N. Y. (2023). Why is inflation so stubborn? cars are part of the answer. https://www.nytimes.com/2023/05/20/business/economy/car-prices-inflation.html.

Toews, D. (2003). The new tarde: sociology after the end of the social. *Theory, Culture & Society*, 20(5):81–98.

TopGear Nederland (2020). Hoeveel auto's zijn er op de wereld? https://topgear.nl/autonieuws/hoeveel-autos-op-de-wereld/.

Toyota Motors (2022). World premiere of all-new prius in japan. https://global.toyota/en/newsroom/toyota/38225618.html.

Venghaus, S., Henseleit, M., and Belka, M. (2022). The impact of climate change awareness on behavioral changes in germany: changing minds or changing behavior? *Energy, Sustainability and Society*, 12(1):8.

Vintró, C., Sanmiquel, L., and Freijó, M. (2014). Environmental sustainability in the mining sector: evidence from catalan companies. *Journal of Cleaner Production*, 84:155–163.

Woo, H., Kim, S. J., and Wang, H. (2021). Understanding the role of service innovation behavior on business customer performance and loyalty. *Industrial Marketing Management*, 93:41–51.