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Working Paper

Climate, Technology and Value: Insights from the First Decade with Mass-Consumption of Electric Vehicles

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Abstract

We investigate empirically whether the market value of electric vehicles, which have rapid technological progress, decline faster over their lifetime than gasoline vehicles, which is a mature technology. We use novel data from the market with the highest market shares for electric vehicles in the world, Norway, from the largest web platform for secondhand vehicles for 2011-2021. The price path of electric vehicles declines faster than gasoline vehicles. This seems to be driven by the electric vehicles with below median driving range. We hypothesize that the large price drop is mainly due to the fast technological improvement of electric vehicles.

JEL-Codes: D120, L600, L620, O330, Q550.

Keywords: energy transition, price, technological progress, low-carbon technologies, electric vehicles, secondhand market, climate policy.

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1 Introduction

Widespread deployment and continued progress of low-carbon technologies are crucial to reduce greenhouse gas emissions (Barrett, 2009; Dhakal et al., 2022; Pathak et al., 2022; Stock, 2020). The adoption of low-carbon small-scale technologies, such as electric vehicles and solar power, has accelerated the last decade. These technologies have improved very fast, both regarding performance and lower costs (e.g. Pathak et al., 2022). Better and cheaper low-carbon technologies enable more consumers to take part in the energy transition – but also make existing goods obsolete faster than before. We investigate how the market value technology throughout the lifetime when the technology is rapidly improving.

In this paper, we specifically investigate the case of electric vehicles. For electric vehicles, the most important improvement the last decade is the increased driving range, which is due to better and cheaper batteries. This has also allowed production of larger models catering to a larger range of consumers. Gasoline vehicles, on the other hand, is a mature technology. By analyzing the secondhand car market, we exploit that vehicles are sold used at different ages, and we can get the picture of the price path during the lifetime. To study the effect of particularly rapid technological progress on market prices, we compare the price path for ten-year-old electric vehicles and gasoline vehicles.

The Norwegian market is the most mature electric vehicle market in the world (IEA, 2022). The market share for battery electric vehicles has been above 10% of new car purchases since 2014 and by the first quarter of 2022 it is 82.9%.[1] We use a novel data set from the largest web platform for secondhand vehicles in Norway, finn.no, accounting for close to 90% of the market, for the years 2011-June 2021. At this platform, the electric vehicle share of the market for vehicles that are 10 years or younger has been above 1% since 2013 and is 23% as of June 2021. The time period 2011-2021 covers the years where electric vehicles have been an important part of the Norwegian market.

We find that used electric vehicles decline faster in price than used gasoline vehicles. This difference seems to be driven by electric vehicles with driving range below 200 km (close to the median range in our sample). When we exclude these vehicles from the sample, electric vehicles no longer decline faster in the price than gasoline vehicles.

To understand the difference in the price decline between the two technologies, we first develop a theoretical framework based on the model of Stolyarov (2002) of the resale pattern of durable goods. As electric cars is a less mature technology than cars based on combustion engines, technological progress is faster. This reduces the utility of used cars relative to that of a new car, and hence leads to reduced demand and increased supply of secondhand cars. To maintain equilibrium in the market of used cars when the technology is improving, the price of used cars has to decrease. Hence the price of electric vehicles drops faster compared to gasoline vehicles.

[1] As of June 2021 where this analysis stops the market share was 57%.

The maturity of a technology might depend on the adoption rates in combination with other factors (Pathak et al., 2022, p. TS-128-129). Therefore the findings of our paper should not be used as an argument for delaying the deployment of new low-carbon technologies. Rather, the findings may be used to inform about the cost of implementing climate policies. The value of the secondhand products matters for the total cost of ownership of the good, which again matters for the cost of climate policy. For instance has the Norwegian government a goal that "purchase of zero-emission cars should be more economically favourable than purchase of conventional car" (Norwegian Ministry of Transport and Communications, 2017). When comparing whether it is favourable to buy an electric vehicle compared to a gasoline vehicle, it is important to take into account also the difference in the value of the used car, not just the price of the new car. This point can be transferred to other low-carbon technologies with fast technological progress. At the same time, many actors are working on finding new business models for batteries that are no longer in use in a car (see for instance Evyon (2022)). This indicates that even if products with fast technological development deteriorates faster, they are not without value.

The technology shift in the Norwegian car market is a prediction of what may happen in other countries if batteries continue to fall in price and policies promoting electric vehicles and charging infrastructure continue. Other important car markets are less than 10 years behind Norway in the electric vehicle adoption. If batteries continue to decline in price, electric vehicles are predicted to become competitive compared to gasoline vehicles by mid-2020s (Bloomberg, 2020; J.P. Morgan, 2018, 2020).[2]

This paper contributes thematically to three different strands of the literature, namely, technological development, durable goods and the car market. In growth theory there is a literature on how technological progress evolves endogenously as resources are spent on R&D (e.g. Aghion & Howitt, 1998). In addition, there is a literature on the interaction between technological change and environmental policy (e.g. Acemoglu et al., 2012). However, in this paper we take the technological process as exogenously given. Our work relates more closely to the work on vintage capital where technological progress only affects the economy through new capital – and where every vintage of capital is marked by the period in which it was produced (Solow et al., 1966). This also leads to the question of optimal replacement of capital (Rust, 1987). Rosenberg (1976) argue that expectations about future technological improvements are of great importance for the firm's decision to adopt technology now or wait for improved technology.[3] De Groote and Verboven (2019) investigate household's investment decision for solar power, which has had, similiar to electric vehicles, increased quality and decreased prices.

Cars are one of the prime examples of durable goods. Waldman (2003) reviews much of the early literature on durable goods, including theories of optimal durability of goods, the effects of a secondhand market on the new goods market, and information problems in the secondhand

[2]However, whether battery prices continue to decline the coming years is not sure (Bloomberg, 2021a, 2021b).
[3]This argument is further developed by Balcer and Lippman (1984).

market. A study that in many ways is close to ours is the one by Fudenberg and Tirole (1998). They consider a monopolist selling goods in two periods with improvements in quality between the two periods. Their focus, however, is on the behavior of the monopolist selling the new good and taking the secondhand market for given whereas we focus on the secondhand market. In a seminal contribution close to our theoretical approach, Stolyarov (2002) develops a model of the resale pattern of durable goods. Goods are purchased new at a fixed price and the quality of the product deteriorates over time.

There is a vast literature on the demand for cars specifically. A starting point is Akerlof's (1970) seminal theoretical study, which in itself is not very relevant to our study. This study was followed up by Bond (1982), who empirically studied the demand for used pickup trucks (see also Bond (1983)). To study whether bad cars are driving out good ones from the secondhand market, he investigates whether secondhand trucks require more maintenance than otherwise similar trucks bought new. He does not find any difference between first- and secondhand bought trucks.

The newer empirical literature on the demand for automobiles is heavily inspired by the study by Berry et al. (1995). In their study, however, they only consider the static demand for new cars. There is also a literature on the pricing behavior of car manufacturers in the presence of a secondhand market (e.g. J. Chen et al., 2013; Esteban & Shum, 2007). Schiraldi (2011) introduce a dynamic element to this class of models. In his model, consumers decide whether to sell or replace their car in every period, and the supply of new cars is constant over time. Gavazza et al. (2014) provide a model of the household's decision about which cars to buy, hold, and sell in the secondhand market in a framework based on Stolyarov (2002). Gillingham et al. (2022) develop a computationally tractable dynamic equilibrium model of the car market with heterogeneous consumers. Our empirical approach is most closely related to the approach followed by Purohit (1992). He estimates the effect of changes such as major styling changes, downsizing and changes in horsepower, in new cars on the price of used cars and finds that enhanced features of new cars increases the obsolescence effect of used cars. The changes he study, however, are minor compared to the technological changes electric vehicles have experienced the last decade.

Our paper is also closely related to the literature on the evolution of the price of used durable goods, particularly cars, over time. Wykoff (1970) studies the declining price of selected car models to study the shape of the depreciation function, whereas Porter and Sattler (1999) study trade in secondhand cars in the late 1980's. Not surprisingly are prices of cars falling over time, but the pattern varies across types of cars. Similar variation is found by Esteban and Shum (2007). Copeland et al. (2011), moreover, document a similar fall in prices for new vehicles.

The literature on technological progress and improvement of durable goods focusing on other goods than cars is also relevant. Gordon (2009) studies the market for replacement of computer CPUs that improve over time, and Gowrisankaran and Rysman (2012) provides a model of the

market for durable goods where the quality of new goods is improving, which resembles the still evolving market for electric cars. However, they do not allow for a secondhand market. Quite similar to our study, Ishihara and Ching (2019) study the market for used video games where newer games are assumed to be better than old games. Their main focus, however, is the effect of the secondhand market on the market for new games. A major difference between automobiles and video games, however, is that users experience satiation from playing a game repeatedly, making games "less durable".

There is also an emerging literature on the demand for electric and "green" cars. Most of this literature, however, suffers from lack of data on observed behavior. Glerum et al. (2014) provides a forecast of future demand for electric vehicles using stated preference survey data. Survey data has also been studied in more sophisticated modelling frameworks (Liu & Cirillo, 2017), and there are studies of specific characteristics such as battery capacity (Danielis et al., 2019). Archsmith et al. (2022) document that the demand for electric vehicles in the US is closely related to environmental preferences, and Holland et al. (2021) build a quantitative model to analyze how different policies affect the transition to electric cars. Brückmann et al. (2021) survey whether fear of not being able to resell an electric vehicle reduces demand for electric vehicles, and find that consumers expect a higher resale value for electric vehicles than conventional cars.

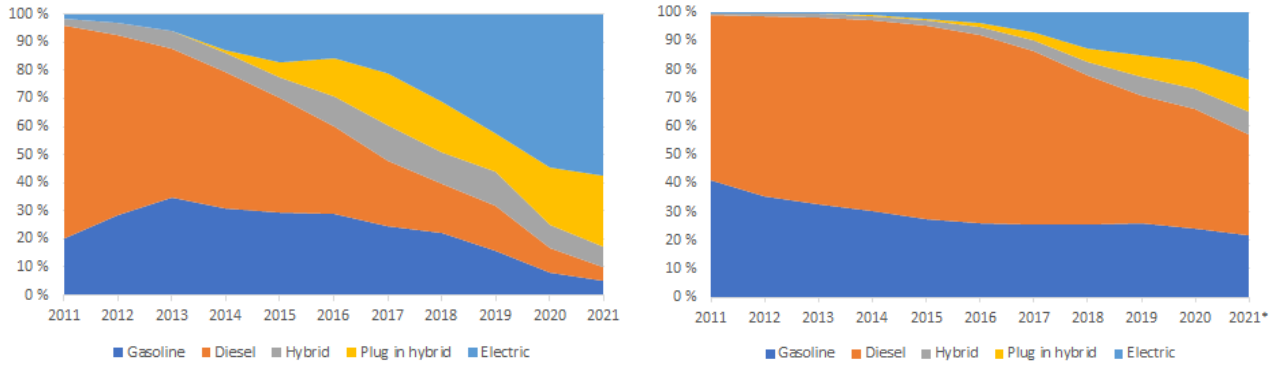
There is also a literature on provision of incentives to replace polluting cars with newer varieties. Adda and Cooper (2000) present a theoretical model with simulations to study the effect of a subsidy program in France. Li et al. (2020) and Mian and Sufi (2012) provide an analysis of the Cash-for-Clunkers program whereas Guan (2021) analyze the CARS program, both in the US. C.-W. Chen et al. (2021) examine the effect of a subsidy program to fuel-efficient cars in China, while Springel (2021) investigates whether subsidies to electric vehicles or charging stations are most important.

In addition, similar to us, Sallee et al. (2016) use used car prices in their analysis, but investigate whether consumers recognize the value of fuel economy. Also Strittmatter and Lechner (2020) use data similar to us and use it to investigate whether there is a sorting in the secondhand car market based on environmental quality.

Our first contribution is to present empirical results that indicate that the price paths of goods that have a large technological improvement each year is different than for goods that do not have large technological improvements from year to year. Second, we contribute to the state of knowledge on the electric vehicle market. Investigating the price path of electric vehicles during the lifetime with information from the most mature electric vehicle market in the world has not been done before and is relevant since this is a technology that probably will be phased into the car market globally the coming decade. Third, we inform the estimation of the cost of climate policy since valuation of the used low-carbon technology is part of the cost.

The structure of the rest of the paper is as follows. First, we give background information about

Figure 1: Sale shares by technology for new and second hand cars in the Norwegian market 2011-2021



(a) New cars

(b) Second hand cars

Notes: Data for 2021 covers January to June.

the car market in Section 2. In Section 3 we present our theoretical framework that we use to make a hypothesis about the cause of the findings. Further, we present the data, descriptive statistics and the empirical strategy in Section 4. In Section 5 we present and discuss the results and in Section 6 we conclude.

2 Background on the car market

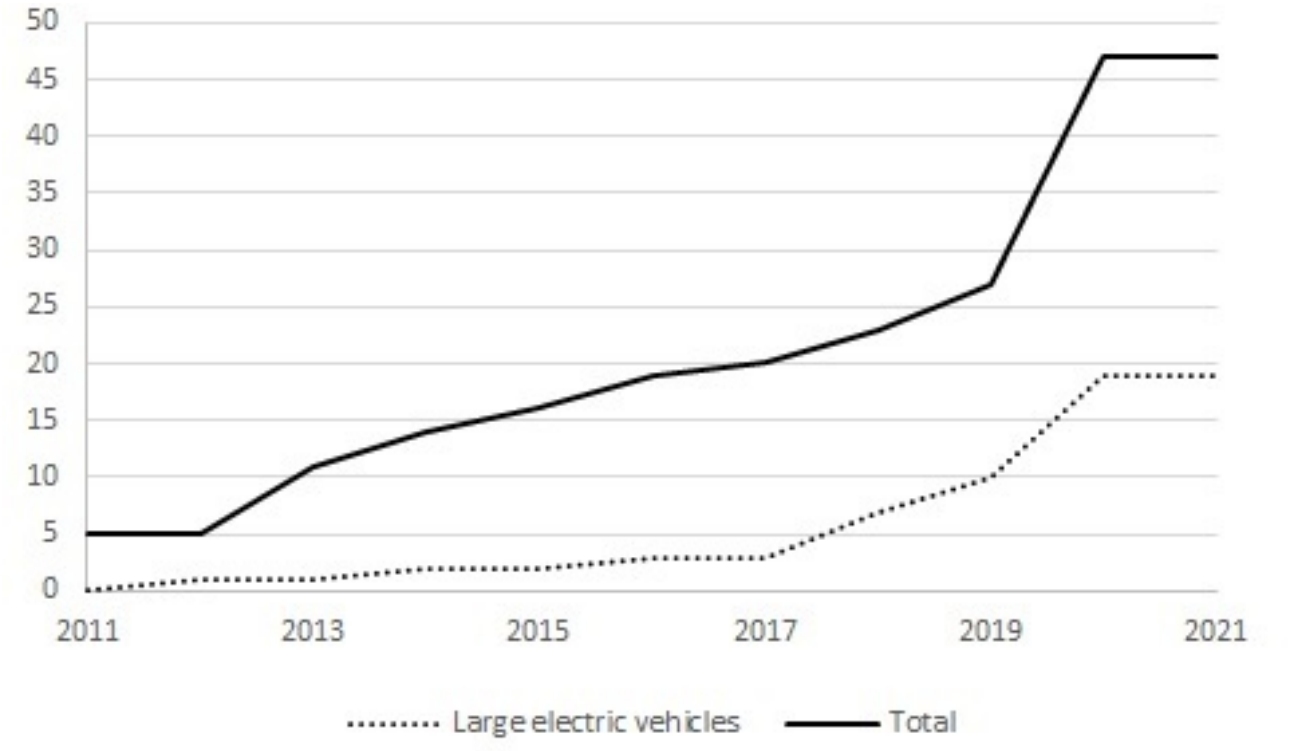
An extraordinary technology shift is expected to happen in the car market. The EU aims to reach net zero emissions by 2050, and the share of zero emission passenger cars in the scenarios reaching net zero by 2050 is 96% (European Commission, 2018, p.119). A car lasts for 15-20 years. For the car fleet to transition to zero emission vehicles, the market share for zero emission vehicles among the new cars sold need to increase first. A large part of this shift has already happened in the Norwegian car market over the last decade. The share of different types of vehicles sold in Norway from 2011 to 2021 can be seen in Figure 1a. From having 96% market share in 2011, gasoline and diesel vehicles have plummeted to a 10% market share. Electric vehicles have increased from a 1.5% market share in 2011 to 57% by June 2021.[4]

The high sale volumes of new electric vehicles extends into the secondhand vehicle market, but naturally there is some delay. The fuel share of the secondhand vehicle market in Norway in 2011-2021 can be seen in Figure 1b, where we for each year show the fuel share of all cars that are below 10 years old that are advertised on the web platform finn.no.[5] The share of electric vehicles hits 1% in 2014, and reached 23% by June 2021. The left part of the graph for new vehicles (Figure 1a) from 2011-2017 looks similar to the right part of the graph for used vehicles from 2014-June 2021 (Figure 1b).

[4]Note that we do not include plug-in hybrids in the electric vehicle category. When we refer to electric vehicles, this is battery electric vehicles. For battery electric and plug-in hybrids the sale share in 2021 (until June) is 80%.

[5]We use the term *fuel* also about electric vehicles, all though strictly speaking electricity is not a fuel.

Figure 2: Number of available electric vehicle models for sale



Notes: Data for 2021 is as by June 2021. Large vehicles are defined as station wagon, SUV, pickup and multipurpose vehicles. Small vehicles are sedan, hatchback, coupe and cabriolet. These are models that are imported by the car manufacturers official seller network. Imported models from other actors are not included here.

The sale shares of electric vehicles in the USA, Korea and Canada in 2021 are equal to the sale shares of new electric vehicles in Norway about ten years ago (IEA, 2022).[6] Globally the sale share of electric vehicles in 2021 is equal to the sale shares in Norway in 2013, while China and Europe are ahead of the USA and have sale shares for electric vehicles in 2021 equal to the sale shares in Norway in 2013-2014 (IEA, 2022). The Netherlands have sale shares for electric vehicles in 2021 that are equal to the Norwegian sale shares in 2017 (IEA, 2022). In addition has Iceland sale shares for electric vehicles in 2021 that are equal to the Norwegian sale shares in 2018 (The Norwegian Electric Vehicle Association, 2022b). Thus, these markets are less than 10 years behind Norway in the electric vehicle roll-out.

Driving range has increased considerably since the market of electric vehicles started to grow in the beginning of the 2010s. In addition, comfort of electric vehicles has increased and the variety of vehicle models available has expanded. In Figure 2 we see the number of electric vehicle models available in the Norwegian market until June 2021. The black line is the total number of electric vehicle models available, while the dotted line is the number of large electric vehicle models available. We see that around 50 electric vehicle models are available in the Norwegian car market. As a comparison there are 153 different models available in 2020 for gasoline vehicles. Thus, the electric vehicle market is maturing, but it is not fully mature yet.

[6]Note again that this is battery electric vehicles, and not plug-in hybrids included.

3 Theoretical framework

In this Section, we present a simple version of Stolyarov's (2002) model tailored to the secondhand market for cars. This is a dynamic model with an infinite time-horizon for the consumers. We focus on the steady state of the model, i.e. the situation where the number of buyers and sellers of new and used cars is constant over time.

A car has a characteristic x we refer to as its quality. The market consists of a continuum of consumers each described by a parameter h which indicates their valuation of cars. The parameter h follows a distribution over some interval $\Omega \subseteq \mathbb{R}_+$ with cumulative distribution function F. We assume no holes and no mass points. A consumer with characteristic h has an instantaneous utility over cars of quality x and consumption c given by

$$U = xh + c, \tag{1}$$

where consumption is the income not spent or car purchases. For simplicity and without loss of generality, utility from other consumption in disregarded in what follows. Consumers have a common discount factor $\beta \in (0, 1)$.

Cars last for two periods. In the first period, they provide a quality x_n. The second period, they deteriorate and provide quality $x_u = \mu x_n$ with $\mu \in (0, 1)$. After two periods, the car provides no further benefit.

3.1 The market for cars without technological progress

Consider first the market for cars that do not have technological progress. This can be seen as conventional cars. The technology in this market is mature, and a new car has the same utility characteristic x_n every period. New cars are sold at some exogenously given price p_n. This could correspond to a small country that acts as a price taker in the global market for cars or a competitive car industry with constant returns to scale. Used cars are traded in the secondhand market at a price p_u.

Assume initially that everybody needs a car. Consumers in the market have three options. They can each period buy a new car and sell it after one period, they can buy a new car and drive it for two periods, or they can every period buy a used car. Let U^N, U^K, and U^O denote the utility of these options. Notice that the K group has no impact on the market for secondhand cars except from being an outside option. We have

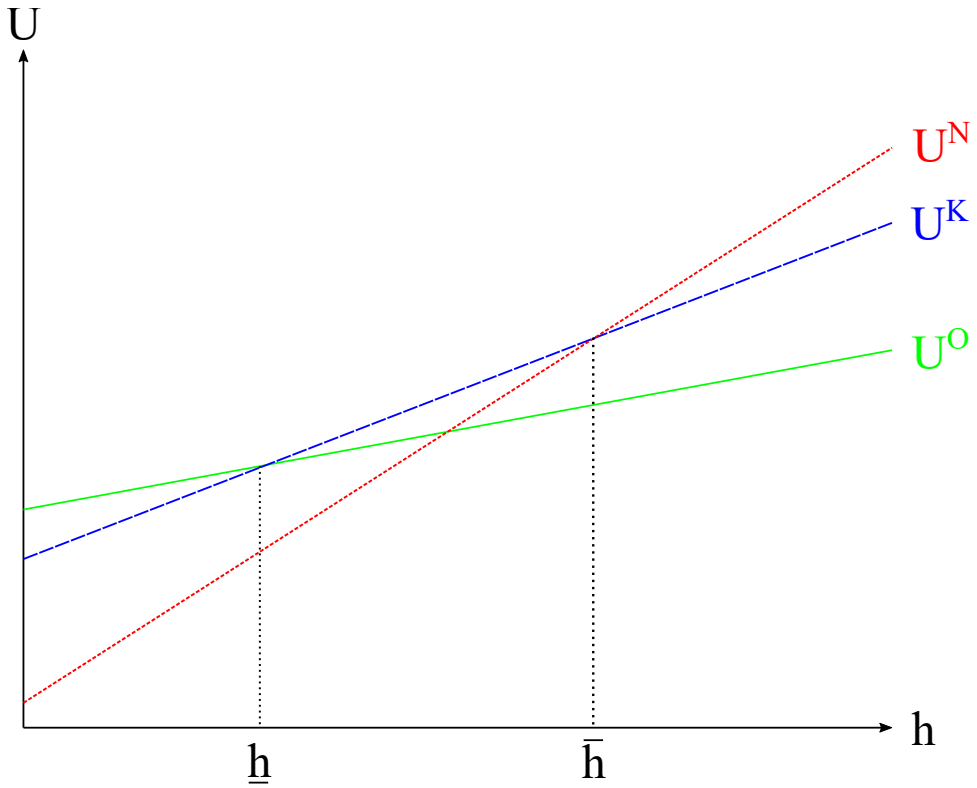
$$U^N = x_n h - p_n + \beta(x_n h - p_n + p_u) \tag{2}$$

$$U^K = x_n h - p_n + \beta x_u h \tag{3}$$

$$U^O = x_u h - p_u + \beta(x_u h - p_u) \tag{4}$$

The utilities as function of h are illustrated in Figure 3.

Figure 3: Utility of various car ownership strategies by h.



Consumers, differentiated though their index h, then choose the option N, K, or O that suits their preferences the best. We solve the model by letting consumers make a plan for two periods. The outcome is, however, dynamically consistent so no consumer would like to change her mind in the second period. Whenever the price of secondhand cars is below the price of new cars ($p_u < p_n$), consumer with $h = 0$ prefers O over K and K over N. As the slope of the utility functions is steeper for the latter two, however, consumers with high valuation of car quality (high h) chooses option N, consumers with intermediate h chooses option K, and low valuation consumers choose option O. Specifically, there are levels $\underline{h}$ and $\bar{h}$ so consumers with $h < \underline{h}$ chooses O, consumers with $\underline{h} < h < \bar{h}$ chooses K, and consumers with $h > \bar{h}$ chooses N. The parameters are defined by indifference, so

$$\begin{aligned} x_u\underline{h} - p_u + \beta(x_u\underline{h} - p_u) &= x_n\underline{h} - p_n + \beta x_u\underline{h} \\ x_n\bar{h} - p_n + \beta(x_n\bar{h} - p_n + p_u) &= x_n\bar{h} - p_n + \beta x_u\bar{h} \end{aligned}$$

yielding

$$\begin{aligned} \underline{h} &= \frac{p_n - (1+\beta)p_u}{x_n - x_u} \\ \bar{h} &= \frac{p_n - p_u}{x_n - x_u}. \end{aligned}$$

Equilibrium in the market for secondhand cars requires that p_u is chosen so the number of sellers

and buyers of secondhand cars, i.e. the groups N and O, are equal. Using the assumption that the quality of cars deteriorate by a factor μ so $x_u = \mu x_n$, this yields the equilibrium condition

$$F\left(\frac{p_n - (1+\beta)p_u}{(1-\mu)x_n}\right) = 1 - F\left(\frac{p_n - p_u}{(1-\mu)x_n}\right) \tag{5}$$

Implicit differentiation of this expression yields

$$\frac{\partial p_u}{\partial \mu} = \frac{f\left(\underline{h}\right)\underline{h} + f\left(\bar{h}\right)\bar{h}}{(1+\beta)f\left(\underline{h}\right) + f\left(\bar{h}\right)} x_n > 0. \tag{6}$$

Hence, as we should expect, if the quality of a car retained after a period increases, the price of secondhand cars also increases.

So far in the analysis, we have assumed that all consumers need a car, hence implicitly that the utility of not owning a car is sufficiently low. In many settings, other means of transportation can be a suitable alternative. To include this in the model, we can introduce an outside opportunity of not owning a car yielding a utility level $\underline{U}$. A full analysis of this case can be found in Appendix A.1. This change to the model does not change any qualitative insights from the model, so to maintain simplicity we disregard the presence of an outside opportunity for the rest of the paper.

The solution studied above is a steady state where the price of secondhand cars remains stable. This is a reasonable description of a mature market. However, at the first introduction of cars to the market, there were of course no secondhand car initially. Subsequently the economy converged to an economy where the three groups N, K, and O obtained stable sizes and hence that prices stabilized. We do not think that this dynamic is particularly enlightening to study formally.

3.2 The market for cars with technological progress

Consider now a market for cars with technological progress, i.e. that the utility of a new car is increasing over time. This market can for example be the case of electric cars. The technological progress can be the general comfort of driving the car, but maybe more relevant is the car's driving range and battery capacity. We use this extension to study the market for electric cars and compare the market for secondhand electric and conventional cars. For analytical tractability, we disregard interaction between the two markets.

To account for technological progress, we assume that the utility characteristic x_n of a new car increases by a rate $\gamma > 1$ every period. Seen from a specific period where new cars have quality x_n, next period's new cars have quality γx_n whereas new cars last period were sold with quality $\frac{x_n}{\gamma}$. We still maintain the assumption of a constant price p_n of new cars and study how the price of secondhand cars depend on the rate of technological progress γ.

This implies two changes for the consumers' choice of car ownership option. Consumers always buying new cars (N) face an improved car technology next period, increasing their willingness to sell their used car on the secondhand market. Consumers always buying used cars (O) face an obsolete used car in every period, reducing their utility of the strategy. The new utilities of the three options become

$$\begin{cases} U^N = x_n h - p_n + \beta[\gamma x_n h - p_n + p_u] \\ U^K = x_n h - p_n + \beta\mu x_n h \\ U^O = \dfrac{\mu}{\gamma} x_n h - p_u + \beta(\mu x_n h - p_u). \end{cases} \tag{7}$$

This yields the cut offs

$$\underline{h} = \frac{p_n - (1+\beta)p_u}{\left(1 - \frac{\mu}{\gamma}\right) x_n}$$
$$\bar{h} = \frac{p_n - p_u}{(\gamma - \mu)x_n}$$

and the equilibrium condition becomes

$$F\left(\frac{p_n - (1+\beta)p_u}{\left(1 - \frac{\mu}{\gamma}\right) x_n}\right) = 1 - F\left(\frac{p_n - p_u}{(\gamma - \mu)x_n}\right) \tag{8}$$

An increase in the rate of technological progress initially reduces the utility of the O option and increases the utility of the N option as illustrated in Figure 4. The utility profile of options N and O shifts to $U^{N'}$ and $U^{O'}$. This leads to reductions in both $\underline{h}$ and $\bar{h}$ to levels $\underline{h}'$ and $\bar{h}'$. The first effect leads to reduced demand for secondhand cars, the second effect to increased supply. To maintain equilibrium, the price of used cars has to decrease. Specifically, we show in Appendix A.2 that

$$\frac{dp_u}{d\gamma} = -x_0 \frac{f(\underline{h})\underline{h}\frac{\mu}{\gamma} + f(\bar{h})\bar{h}}{f(\underline{h})(1+\beta)(\gamma) + f(\bar{h})} < 0 \tag{9}$$

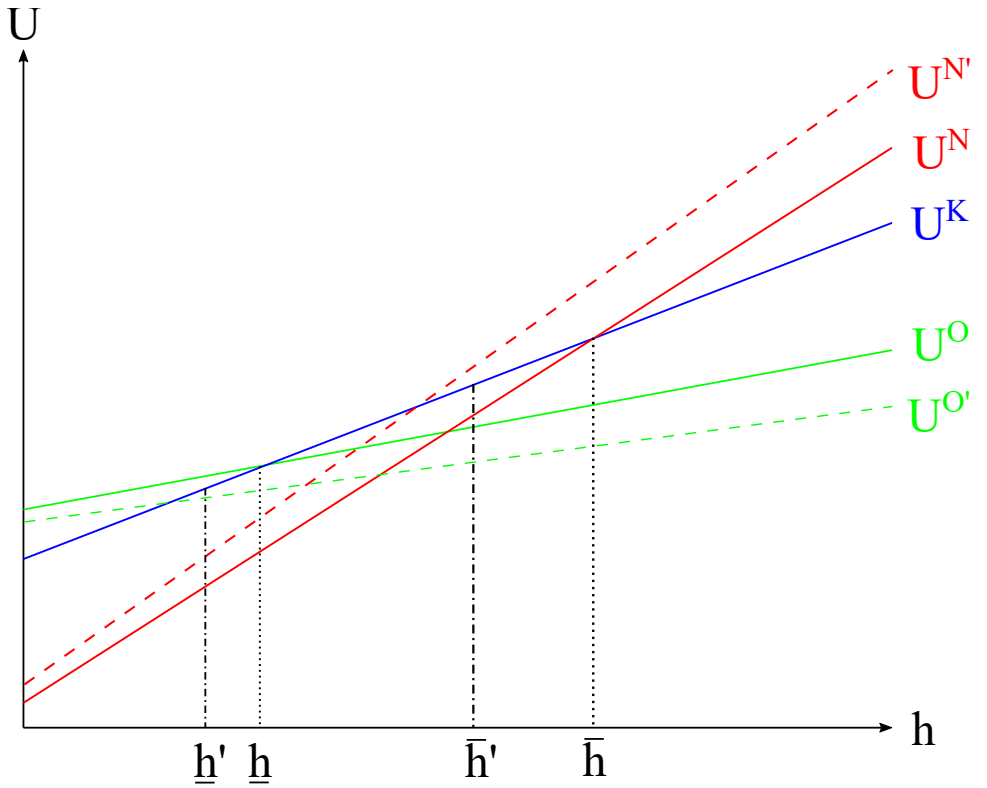
To see how the speed of technological progress γ affects the size of the secondhand market, we can study $\frac{d\bar{h}}{d\gamma}$. As shown in Appendix A.2, the total effect of increased technological progress on the cut-off for always purchasing a new car can be written as

$$\frac{d\bar{h}}{d\gamma} = -\frac{f(\underline{h})}{(\gamma - \mu)} \times \frac{(1+\beta)\gamma\bar{h} - \frac{\mu}{\gamma}\underline{h}}{f(\underline{h})(1+\beta)\gamma + f(\bar{h})}$$

As $(1+\beta)\gamma\bar{h} > \frac{\mu}{\gamma}\underline{h}$, we get $\frac{d\bar{h}}{d\gamma} < 0$.

The increase in γ increases the utility of new cars and hence tends to reduce $\bar{h}$ as more consumers

Figure 4: The effect of technological progress on the utility of car ownership strategies



Notes: The dashed lines indicate the shift in utility resulting from in increase in the rate of technological progress γ. Subsequent price effects are not shown.

enter into the N segment. This is the effect illustrated in Figure 4. To maintain equilibrium, the fraction of consumers who always buy used cars (U) increase equivalently, whereas the fraction of consumers who buy new cars and stick with them (K) declines. This is partially offset by a reduction in p_u as it increases the relative price of a new car. This effect, however, is a consequence of the first effect and hence cannot dominate.

This finding is intuitive because the utility of owning a new car increases with technological progress and therefore more people than without technological progress decide to not stick with the car they bought for two periods, but rather decide to buy a new car each period. These are the consumers with quite high values of h, the utility weight on the car's quality.

With the price decline for used cars, consumers who in the market without technological progress would buy a new car in the first period and stick with it for the next, decide to rather buy used cars in both periods. These are the consumers with quite low levels of h. The model therefore predicts larger turnover and a larger second hand market for cars when there is large technological progress.

3.3 Multiple vehicle technologies in the same marked

The market we study empirically consists of cars using different fuel types, where our main focus is the difference between electric and gasoline cars. In the model above, we model these

as cars where technological progress is still ongoing (immature technologies) and models where technological progress to a larger extent has stagnated (mature technologies). Hence, the consumer has a choice not only between a new and a secondhand car, but also between models where technological progress differs. We do not present a full model of this case but discuss how the preceding framework can be used to understand it.

If the models with technological progress maintain a constant rate of technological improvement, they will eventually completely fill the market at the expense of cars without technological progress. A complete model would have to take this into account, modelling the technological progress as a transition towards a steady state with mature technology that remains at a constant level.

To model that there are consumers preferring both types of cars, we extend the model to the utility function of driving a car with immature technology to

$$U = xh + c + \epsilon,$$

where ϵ, the net utility of the immature technology compared to the mature technology, has a distribution in the population. In general, ϵ can take on any real value indicating either a preference in the direction of mature or immature technologies. This term can be related to technology specific preferences, characteristics such as noise or emission level as well as social image associated with the technology. The utility of driving a car with mature technology remains the same. The prices of new cars of both types are given exogenously. We now find six choice set for consumers. Consumers can purchase a new car every period and sell it in the secondhand market at the end of the period (N), purchase a used car in the secondhand market every period (O), or purchase a new car every second period and keep it for two periods (K). In all three cases, the consumer can buy a car with mature (m) or immature ($\bar{m}$) technology.

As above, an interesting experiment is to study the effect of increased technological progress γ on the various prices. As for the case with only immature technologies, an increase in γ makes it more attractive to purchase an $\bar{m}$ type car, moving consumers from $K_{\bar{m}}$ to $N_{\bar{m}}$. Second, the increase in γ makes new $\bar{m}$ cars more attractive than new m cars , moving some consumers from N_m to $N_{\bar{m}}$. Both effects increases the supply of secondhand $\bar{m}$ cars. The second effect also reduces the supply of secondhand m cars. To maintain equilibrium in the markets for secondhand cars, we need increased demand of secondhand $\bar{m}$ cars. Hence, the price of secondhand $\bar{m}$ cars goes down.

We should also see an increase in the price of secondhand m cars as their supply is reduced. Hence as long as electric cars undergo more rapid technological progress than gasoline cars, we expect the price of secondhand electric cars to decrease relative the price of secondhand gasoline cars.

4 Data, descriptive statistics and empirical strategy

4.1 Data

In our analysis we use a novel data set from the largest web platform for secondhand vehicles in Norway, finn.no, which accounts for close to 90% of the secondhand car market. This is the first time the data is used for this kind of analysis.

The data cover the period January 2011 to June 2021. We start our analysis in 2011 because Nissan Leaf was introduced to the Norwegian market in the end of 2011.[7] Nissan Leaf was the first modern electric five-seat vehicle to be produced for the mass market from a major manufacturer.

We analyze passenger vehicles sold as new in 2011 or later. This means that we only have vehicles that are 10 years or younger in our analysis. The total number of observations in the data is 5.5 million, meaning that there are on average 500 000 ads for secondhand vehicles on finn.no each year. Around 3.4 million cars are older than 10 years and around 800 000 of the 2.1 million that are left are duplicates because the car is advertised for more than one month. Then the total number of observations is 1.3 million. The vehicles that are gasoline or electric vehicles and 10 years or younger are in total around 450 000 observations. The number of vehicles of the different fuels can be seen in Appendix Table A-3.

In addition, we have list prices for new vehicles from The Norwegian Road Federation (OFV). The Norwegian Road Federation is a membership organization for car importers, transport companies and other actors within transport, and have a role as producer of statistics about the car sale in Norway. They also gather price information from the car importers and delivers the official list prices to the tax authorities that use them to calculate wealth tax. The data from The Norwegian Road Federation also categorizes the vehicles into different body style categories.[8]

Further, we have information about the driving range of the electric vehicles, collected from the Norwegian Electric Vehicle Association's website that informs about the different electric vehicle models (The Norwegian Electric Vehicle Association, 2022a).[9] We also have access to a survey among Norwegian electric vehicle owners conducted by the Norwegian Electric Vehicle Association. There is around 15 000 respondents in the survey.[10] Additional details about the data and the variables can be found in Appendix B.

[7] Nissan Leaf was first sold to the Japanese and American market in the end of 2010.

[8] The vehicle body is the main supporting structure of the car (such as windows, doors, engine cover, roof and luggage cover) and defines the shape and the size of the car. The body style can be used to classify the car market into different segments or size classes. However, in Europe there is no official definition of size classes based on objective criteria. See Appendix B.2.3 for more details on this issue.

[9] The standard for measuring driving range is WLTP and if NEDC is the only number available, we reduce the driving range by a factor of 0.65 (J.D. Power, 2020).

[10] 2021: 15 464 respondents, 2020: 14 170 respondents, 2019: 16 216 respondents.

Notice that information on some variables is incomplete. From the platform data, we have the prices requested by the seller. This is not necessarily the price the vehicle is actually sold for as there can be haggling over the prices. However, measurement error in the outcome variable is generally unproblematic as long as this is not a systematic measurement error. Further, we don't know whether a transaction has actually taken place, but for most it probably has. We leave out the vehicles that takes more than a month to be sold if the price is not reduced.

Most cars come in different trims, which are different versions for each models with different equipment level. We do not have consistent data on trim levels of the model that is advertised. As the price of the new vehicle can vary a lot depending on trim, but also e.g. battery capacity, engine size and body style, the price of the new vehicle can have a large interval. We take this into account in one empirical specification by removing models where the relative difference between the maximum and the minimum price of one model exceeds 1.5. This does not change the result much.

4.2 Descriptive statistics

In the analysis we compare electric vehicles and gasoline vehicles. Cars of both fuel types are maximum 10 years old. There are roughly 289 000 gasoline vehicles and 156 000 electric vehicles in the sample, which means that the share of electric vehicles in the sample is around 1/3 and gasoline vehicles around 2/3 (see Table 1). Among the gasoline vehicles, about 2/3 are small and 1/3 is large, while for electric vehicles there are fewer large vehicles available (11% of the sample), which is natural when we recall that the supply of large electric vehicles has been limited up until recently.[11] In 2011 there are 27 times more gasoline vehicles as electric vehicles. By 2016, this number is reduced to 4, while there are more electric vehicles than gasoline vehicles sold in 2021 (see Table A-4 in Appendix C).

Table 1: Number of vehicles based on size

	Gasoline	Electric	Gasoline	Electric
Total	295 350	157 393	65%	35%
Small	200 651	137 266	68%	87%
Large	90 483	17 422	31%	11%
Not categorized into size classes	4 216	2 705	1%	2%

Small: Sedan, coupe, cabriolet and hatchback.

Large: SUV, station wagon, multipurpose vehicle and pickup.

Electric vehicles in the sample are younger than the gasoline vehicles. Average age is 2.7 for electric vehicles, while for gasoline vehicles the average age is 3.5, see more details in Table A-5. The number of secondhand vehicles that are from 2011 or later that are advertised on finn.no

[11] Small cars are defined as sedan, hatchback, coupe and cabriolet, while large cars are defined as station wagon, SUV, pickup and multipurpose vehicles. We have done this categorization.

Table 2: The electric vehicle sample

	Number of vehicles	Share of electric vehicles	Mean age
Range below 200 km	88 173	56.0%	3.39
Range [200 km-300 km)	16 396	10.4%	1.42
Range [300- 400 km)	26 908	17.1%	2.37
Range [400- 500 km)	15 755	10.0%	1.05
Range equal to or over 500 km	9 709	6.2%	1.61
Range missing	452	0.3%	3.63

every year can be seen in Table A-4 in the Appendix. 56% of the electric vehicle sample has range below 200 km and only 16.2% 400 km or above (Table 2). The mean driving range each year is lower for the used vehicles than the new vehicles, which underlines the fast technological development, see Appendix Table A-6.

The market for gasoline vehicles are more varied then the market for electric vehicles, which is natural when we recall that there are fewer electric models available than gasoline models. The secondhand electric vehicle market is dominated by Nissan Leaf with about 1/5 of the market. In Appendix Table A-8 we see the top ten models in the secondhand market for electric and gasoline vehicles.

4.3 Empirical strategy

A car i is sold new (time $t = 0$) at an exogenously given price P_{i0}. We assume that the resale value follows a process so that at time t it is

$$P_{it} = A_i B_i^t P_{i0}^{\mu} e^{\epsilon_{it}}, \tag{10}$$

where A_i is car specific characteristics. We assume that secondhand vehicle prices decay exponentially with an annual rate $1 - B_i$. The rate is potentially make specific, but for most of our analysis we only consider fuel specific rates. The parameter μ is the pass-through of the new price, and ϵ_{it} is the stochastic error term.

In order to find the annual percentage drop in prices, we take the logarithm of equation (10) which leads us to the following equation where lower case letters denote logs of variables:

$$p_{it} = a_i + \beta_i t + \mu p_{i0} + \epsilon_{it} \tag{11}$$

The key parameter of interest is β_i, the annual percentage decline in prices.[12] To complete our empirical specification, we also include a measure of log mileage, m_{it}, at the time the vehicle is sold in the secondhand market. Then a vehicle i of make m with fuel type f and body style

[12] As long as β_i is small, we have $\beta \approx ln(1 + \beta)$ or $\beta_i = ln(B_i) \approx B_i - 1$.

category s sold in year t from a dealer[13] of type d that was new in year n gets a price

$$p_{i,t} = \beta_f t + \alpha_{t\times f} + \theta_m + \zeta_s + \omega_d + \mu p_{i,n} + \gamma_f m_i + \epsilon_{i,t} \tag{12}$$

The fixed effects are captured by the terms $\alpha_{t\times f}, \theta_m, \zeta_s, \xi_t$, and ω_d. The error terms are clustered on the make (m).

If price at time n, $p_{i,n}$, is unknown for some reason, we introduce a dummy for missing variables. This implies simply following the price path downward without information of the initial price.

We could also use the price on the same car model as new at the same time as when the used car is sold, rather than when the used car was new. However, the correlation coefficient between the price when the car was new and the price of the new car when the car was sold is above 0.9. Therefore we use the price when the used car is new.

Factors that probably influence the secondhand vehicle price that is not directly part of Equation 12 is quality of the car and the price on substitutes (both used and new). Quality is not measured, but the price of the new vehicle can be seen as a proxy for quality and other characteristics of the car. The quality will probably represent important heterogeneity in the annual price fall (β_f). The price on substitutes (both used and new) is in the error term. We do not expect the price on the substitutes to be correlated with the age of the secondhand car. Therefore the price on substitutes will not bias the estimate on β_f. If the price on substitutes influence the price on new vehicles, there will be a correlation between the new price and the error term, possibly biasing the coefficient on the price on the new vehicle.

5 Results

5.1 Main results

In Table 3 we present the results of the regression equation (12). Gasoline vehicles is the baseline, and we see that the annual price drop for gasoline vehicles is approximately 10-11%. The price on electric vehicles fall around 4.5-6% more than gasoline vehicles, which is 16-17% annually. The difference between gasoline and electric vehicles is statistically significant at least on a 5% level in all specifications, giving a clear indication that electric cars fall more quickly in price than gasoline cars.

In column (1) we control for year $\times$ fuel fixed effects, which absorb influences of all omitted variables that differ from one year to the next for each fuel type but are constant over all vehicles of the same fuel type in each year. This can for instance be development of fast

[13]There are three different dealer categories: private seller, professional importer of that specific brand and professional car sellers, and there might be selection into what cars are sold from which type of seller. There is a statistically significant difference between the price fall of the different sellers, as shown in Table A-19 in Appendix D, so we believe it is useful to control for the dealer type. The share of vehicles based on seller can be seen in Table A-7.

charging stations or other year specific events for electric vehicles. In addition, we control for dealer fixed effects in all specifications, except in column (5), where we show the results without dealer fixed effects.

In column (2) we add body style fixed effects to year × fuel fixed effects.[14] The difference between gasoline and electric vehicles does not change much compared to column (1).

In column (3) we add make fixed effects to year × fuel fixed effects. The dummy variables for the makes absorb the influences of all omitted variables that differ from make to make, but are constant over time. The difference between gasoline and electric vehicles reduces by 1.76 percentage points compared to column (1), indicating that the price fall varies between different makes and when only looking at the price fall within each make, the price fall on electric vehicles is lower (but slightly higher for gasoline vehicles). However, the difference in price fall between electric and gasoline vehicles is still statistical significant. We investigate the price fall for specific makes further in Appendix Figure A-5 and in Appendix Section D.1.

In column (4), we take out the vehicles that have a large variation in new vehicle prices. This reduces the sample from around 450 000 to around 280 000. It could be that the models that vary a lot in prices as new also have other characteristics that influence the price decline, so this is not our main specification, but a robustness test. We see that the coefficients do not change a lot and that the difference is still statistically significant.

In column (5), we show the results without controlling for dealer fixed effects. The difference between electric and gasoline vehicles stay in the same magnitude and remain statistically significant.

We see that mileage is not an important factor for the price of used gasoline vehicles, and even less important for electric vehicles, when age is taken into account. Each percentage increase in mileage is associated with a price fall of around 0.07% for gasoline vehicles. This might be due to age and mileage being closely correlated (see Appendix Figure A-1). For electric vehicles mileage is not statistically significant in any of the specifications in Table 3, but in some other specifications. However, the magnitude of the effect is small.

In Figure 5 we show the results from a regression with age dummies interacted with the fuel type. We control for mileage interacted with fuel, new vehicle price, a dummy on those with missing on mileage and new vehicle price, year × fuel fixed effects and dealer fixed effects. We see that electric vehicles drop faster in price compared to gasoline vehicles. Moreover, the price decline appears to increase over time. The price fall curve seem to be concave and in Table A-9 in Appendix D we investigate whether the concavity is statistically significant by adding an age squared term. The concavity is statistically significant for both technologies, and electric vehicles are statistically significant more concave than gasoline vehicles.

[14]There are eight different body style categories: sedan, hatchback, coupe, cabriolet, station wagon, SUV, pickup and multipurpose vehicles, defined by The Norwegian Road Federation (OFV), see Appendix B.2.3.

Table 3: Comparing gasoline and electric vehicles.

	(1)	(2)	(3)	(4)	(5)
Age	-0.108	-0.106	-0.112	-0.114	-0.115
	(0.00463)	(0.00430)	(0.00400)	(0.00571)	(0.00445)
Electric × Age	-0.0622	-0.0618	-0.0446	-0.0571	-0.0567
	(0.0193)	(0.0198)	(0.0204)	(0.0175)	(0.0199)
Ln new price	1.070	1.050	0.999	1.091	1.063
	(0.0252)	(0.0312)	(0.0319)	(0.0306)	(0.0249)
Ln mileage × Gasoline	-0.0767	-0.0772	-0.0750	-0.0613	-0.0773
	(0.00761)	(0.00648)	(0.00752)	(0.00577)	(0.00760)
Ln mileage × Electric	0.0179	0.0199	-0.00372	0.0138	0.0109
	(0.0123)	(0.0126)	(0.00862)	(0.0149)	(0.0123)
Year × fuel fixed effects	Y	Y	Y	Y	Y
Dealer fixed effects	Y	Y	Y	Y	N
Body style fixed effects	N	Y	N	N	N
Make fixed effects	N	N	Y	N	N
Taken out those with large variation in new vehicle price and those without new vehicle price	N	N	N	Y	N
Observations	452 743	452 743	452 743	283 785	452 743
R^2	0.859	0.861	0.878	0.899	0.857

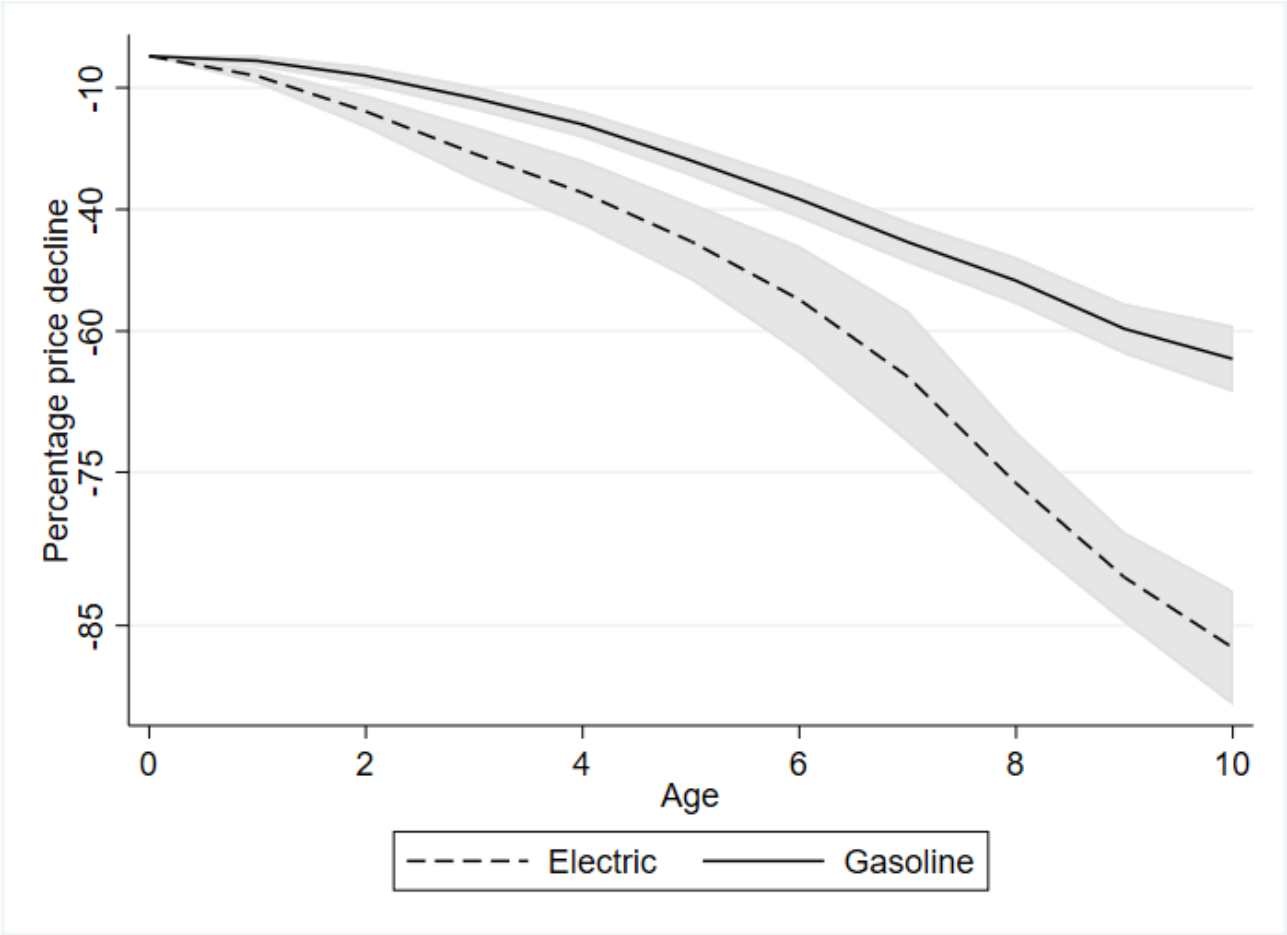
Dependent variable is ln of the secondhand price.

Standard errors clustered on make, in parentheses. There are 62 clusters in all but specification (4), where there are 44 clusters.

Gasoline vehicles are the baseline. Year fixed effects are based on the year the vehicle is sold/advertised.

We use a dummy on those observations that have missing mileage and those that have missing new car price.

Figure 5: The price path for gasoline and electric vehicles

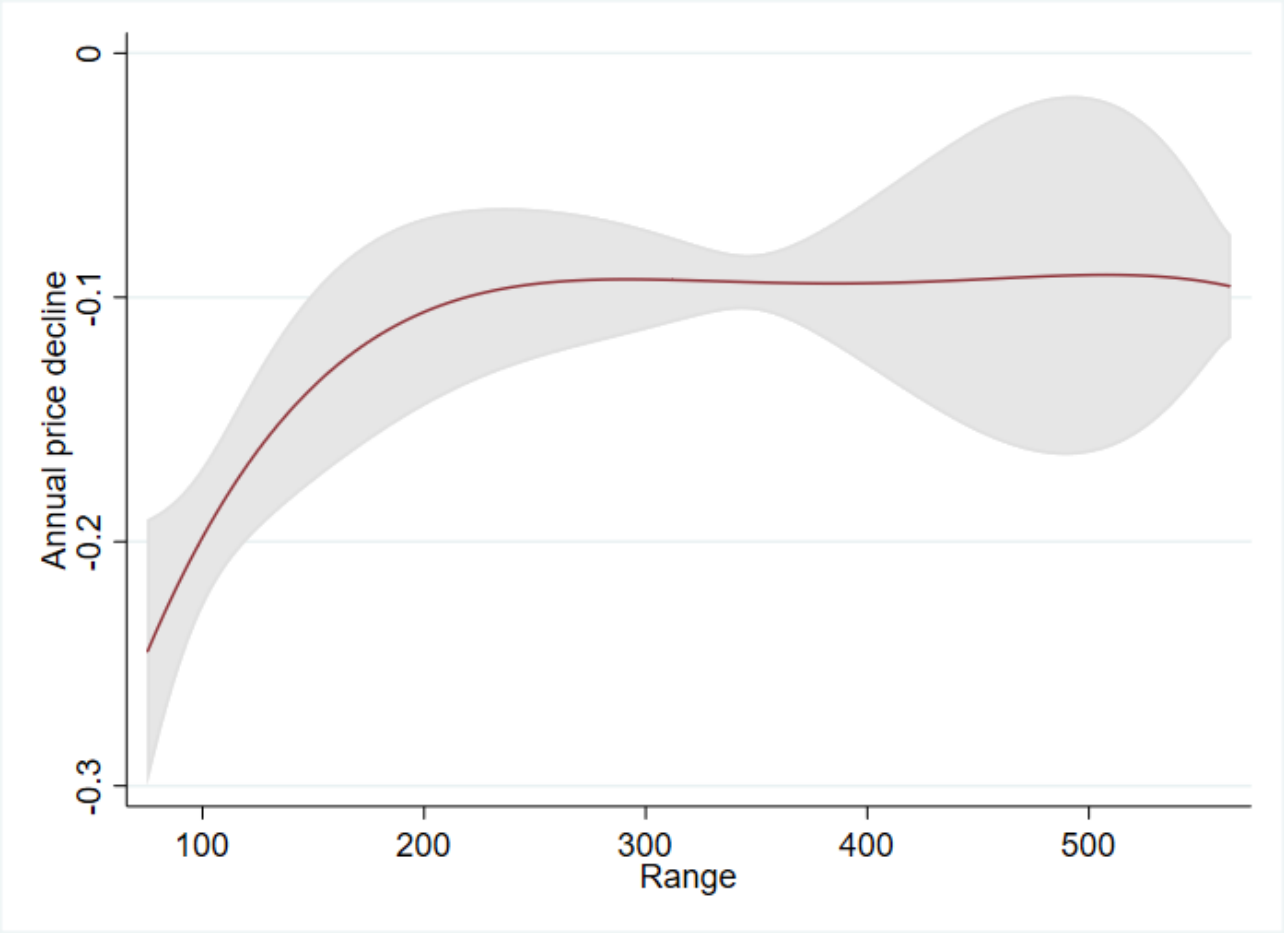


Notes: The grey areas are 95% confidence intervals. The standard errors are clustered on make. There are 62 clusters. The regression includes year times fuel fixed effects and dealer fixed effects and we control for mileage, vehicle price when new and whether the new vehicle price or mileage is missing.

One factor that has increased significantly over the 10 years we look into, is driving range. Range can be seen as a proxy for technological development. We investigate whether the price decline is different for different ranges. Figure 6 show the regression in Equation 12 with a fourth grade polynomial of range interacted with age. This Figure shows clearly that it is the vehicles with range below 200 km that has the largest price decline. The secondhand prices on vehicles with range over approximately 200 km decline at the same level as gasoline vehicles (around 10% annually, see Table 3). However, over half of the electric vehicle sample is vehicles with range below 200 km. The vehicles with range from 200 km and upwards have mean age of 1.74 years, median of 1 year and the highest age is 8 years. We therefore do not have a sample where those with the longer range than 200 km have been in the car market for many years. This is therefore an important question for further investigation when the electric vehicle market has developed further.

In Figure 7 we see that when we take out the electric vehicles with range below 200 km of the analysis, the difference in price decline between gasoline and electric vehicles is no longer present. In Appendix Table A-10 we have the same sample, and the electric vehicles actually

Figure 6: The price decline for electric cars with different driving range.



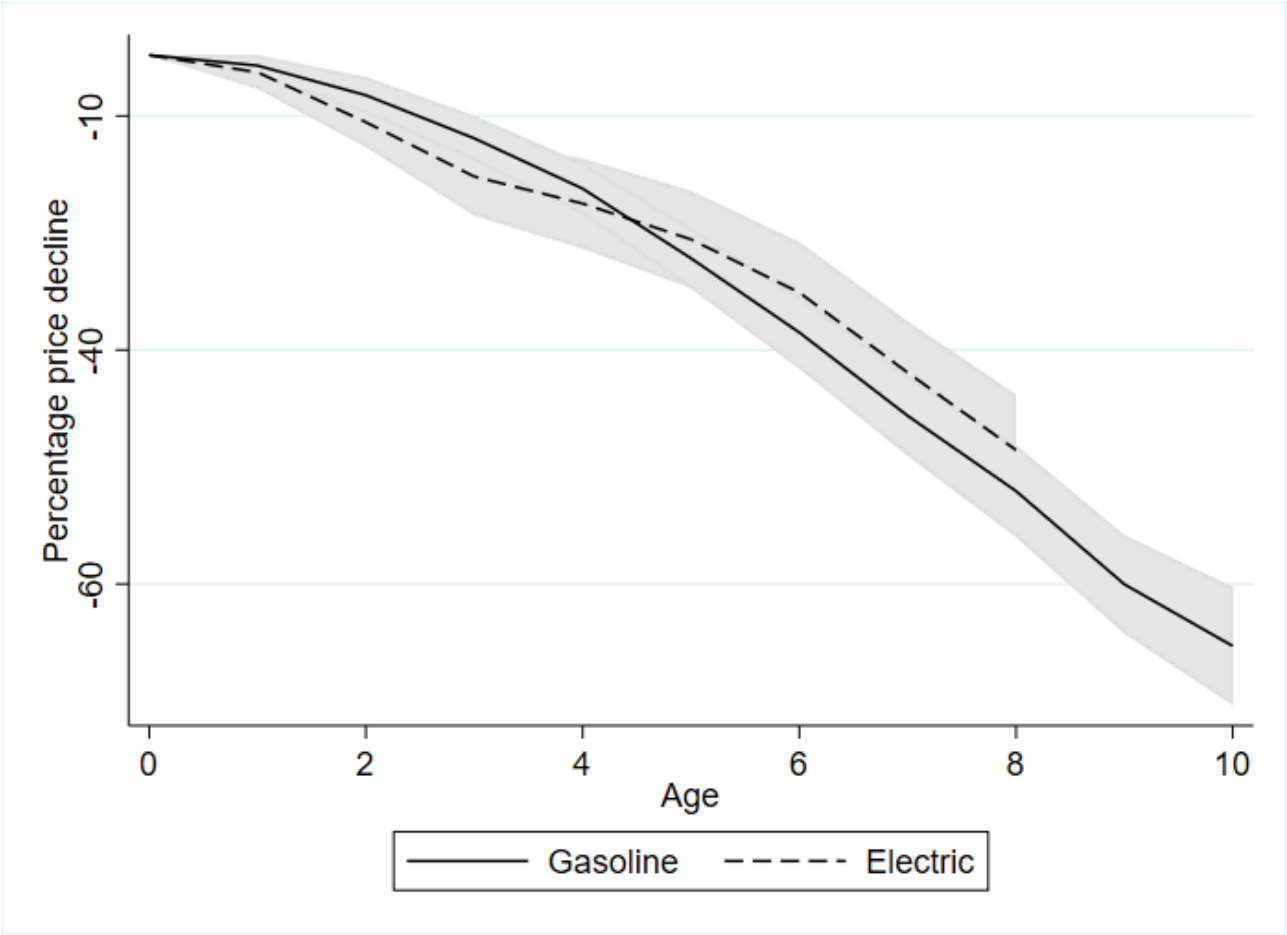
Notes: This is the regression in Equation 12 with a fourth grade polynomial of range interacted with age. Range is in km divided by 100 and WLTP standard. If NEDC is the only available range, we reduce the range by a factor of 0.65 (J.D. Power, 2020). The grey areas are 95% confidence intervals. We start the graph where the sample range start: 76 km range. There are 28 observations with 663 km range. The rest of the sample has a maximum of 564 km. Therefore the graph ends at 564 km.

decline less in price than gasoline vehicles. However, the comparison between electric and gasoline vehicles might not be of same-sized cars, as electric vehicles with range below 200 km are small cars, while for gasoline vehicles the sample is all sizes.

5.2 Additional findings

We show conditional quantile regression on the 25th, 50th, 75th and 90th percentile in Appendix Table A-11. Instead of estimating the mean of the used vehicles price, as OLS does, quantile regression in this case estimates the median, the 25th, 75th and the 90th percentile of the used vehicle price conditional on age and the other control variables. The quantile regression shows a clear pattern: the least expensive electric vehicles have a larger price decline compared to gasoline vehicles than the most expensive cars. Price and range are highly correlated. The price fall difference between gasoline and electric vehicles is statistically significant for all percentiles we have investigated.

Figure 7: The price path for electric vehicles with range from 200 km and upwards and gasoline vehicles.



Notes: The range is measured with WLTP standard. If NEDC is the only available range, we reduce the range by a factor of 0.65 (J.D. Power, 2020). The grey areas are 95% confidence intervals. The standard errors are clustered on make. There are 59 clusters. The curve for electric vehicles stop at 8 years because there is no older electric vehicles with range from 200 km and more. The regression includes year times fuel fixed effects and dealer fixed effects and we control for mileage, vehicle price when new and whether the new vehicle price or mileage is missing.

We compare different size categories based on either body style or weight in Appendix Table A-12. Large electric vehicles do not have a statistically significant larger price fall than gasoline vehicles. Depending on how size is defined, it might seem that large electric vehicles have a smaller price decline than large gasoline vehicles. However, this is uncertain as electric vehicle with the same size as a gasoline vehicle weigh more due to the batteries, but it is uncertain exactly how much more.

We investigate whether there are vintage effects. With vintage effects we mean that there are difference price decline pattern for the vehicles that are new in the first part of the period (2011-2015) than the vehicles that are new in the second part (2016-2021). The results are shown in Table A-13. We see that the price decline of electric vehicles compared to gasoline vehicles in the first period is actually smaller than in the second period. However, when we

include make fixed effects, there is no difference. That means that we can not find vintage effects when we compare price drop within each make.

We split the sample into different subgroups in order to investigate whether and how the price decline difference between the two technologies are present in different subgroups. We compare vehicles in different price categories when they were new in Appendix Table A-14.[15] For the vehicles that are priced when new equal to or above the median or equal to or above the 75th percentile the electric vehicles decline less in price than the gasoline vehicles. For vehicles that are below the median in new vehicle price the electric vehicles decline more than gasoline vehicles. This can be due to range, but also other factors. We see in Table A-6 that there is a large difference in range for the cars that are above and below the median. We also group the sample into different time periods based on when they were new (Appendix Table A-15), when they were sold (Appendix Table A-16) and different age groups (Appendix Table A-17). The difference in price fall between gasoline and electric vehicles is statistically significant for all subgroups.

5.3 Diesel and other fuels

We compare electric vehicles with gasoline vehicles which is a mature technology. Diesel vehicles could also be included in the analysis, but the price path of diesel vehicles will not just represent vehicle technology that are mature, but a vehicle technology that policymakers want to phase out, to a larger degree than gasoline vehicles. Diesel cars had a large advantage from the Norwegian car tax system in 2007-2011, and the diesel share of the new car market was above 70% during this period. From 2012 the car tax system was changed in order to reduce the diesel share. Because other things than being a mature technology is important for the price path of diesel vehicles, they are not in the main analysis.

We present the results for diesel vehicles and the other fuels in Table A-18 in Appendix D. This shows that electric vehicles fall more in price than all other fuel types, including diesel vehicles. However, the difference in price drop between diesel and electric vehicles is not statistically significant in all specifications.

5.4 Other factors affecting the price path

5.4.1 Battery degradation

Degraded batteries or a worry of degraded batteries may be a reason for the price fall on electric vehicles. Degradation of batteries was a concern when the modern electric vehicles market had just started, but anecdotal evidence in the media and correspondence with experts in the sector point in the direction that rapid degradation, rendering batteries useless, is not

[15] We have calculated the statistics for new vehicle price weighted by the vehicles of all fuel types that are advertized on finn.no. The statistics is not differentiated by fuel.

a large problem (Kelleher Environmental, 2019).[16] However, this is a question that warrants further investigation.

The warranty that are given by the car manufacturers can give some indication of the life length of batteries. Nissan has a warranty of 8 years for the vehicles sold in 2016 and onward,[17] guaranteeing the batteries are 75% of its original state. From 2014 Tesla has a warranty that the battery maintain 70% of its original state for 8 years or a kilometer stand of 160 000-240 000 km depending on the model. Hyundai Ioniq guarantees 8 years/200 000 km. This indicates that the car sellers are confident about the battery lifetime.

Even though the batteries last long, a 25-30% degradation of the batteries might be enough to reduce the price of the vehicle, especially if the range is already quite low. Whether this is the case cannot be found with the data from finn.no. To investigate the battery question further, we have looked into a survey among Norwegian electric vehicle owners conducted by the Norwegian Electric Vehicle Association.[18] For the years 2019-2021 they were asked whether the battery capacity in their car has become considerably lower since it was new.[19] Notice that the survey does not provide a clear definition of the term "considerably lower". Still it gives an indication of the state of the battery. Respondents answer on a 1-5 Likert scale range, and the higher the score the better experience do the consumer have with the battery.

In Figure 8 we see the share of respondents who experience that the battery capacity is considerably lower since the car was new (answering 1 or 2 on the survey question). When the car is between 0-3 years the share is around or below 10%. Between 4 and 6 years the share is lower than 30%. Between 7 and 8 years-old the share is between 20 and 45%. The 9 year-olds have shares between 50 and 60% and 10 year-olds down to 37%. However, the sample size is low for the 9 and 10 year-olds (below 100 for each year).

The mean score for 5 year-old electric vehicles is 3.4 in 2021, 3.5 in 2020 and 3.8 in 2019, which means that the mean score has gone down from 2019 to 2021. This can be seen in Figure A-4 in Appendix D. The mean score for 8 year-old electric vehicles is 3.3 in 2021 and 2.9 in 2019 and 2020, which means that the mean score has gone up from 2019 to 2021. For nine year old cars the score is lower with 2.5 in 2021 and 2.8 in 2020, but again: the sample size is low.

From this information we cannot exclude the possibility that some of the price fall for electric vehicles is due to some degradation of the batteries, but the information does not indicate that degradation of the batteries drives the whole price fall on electric vehicles. However, we can not be conclusive on this matter. Another important point is that cars with short range has to be charged more often than cars with longer range. Therefore, as charging reduces the quality of

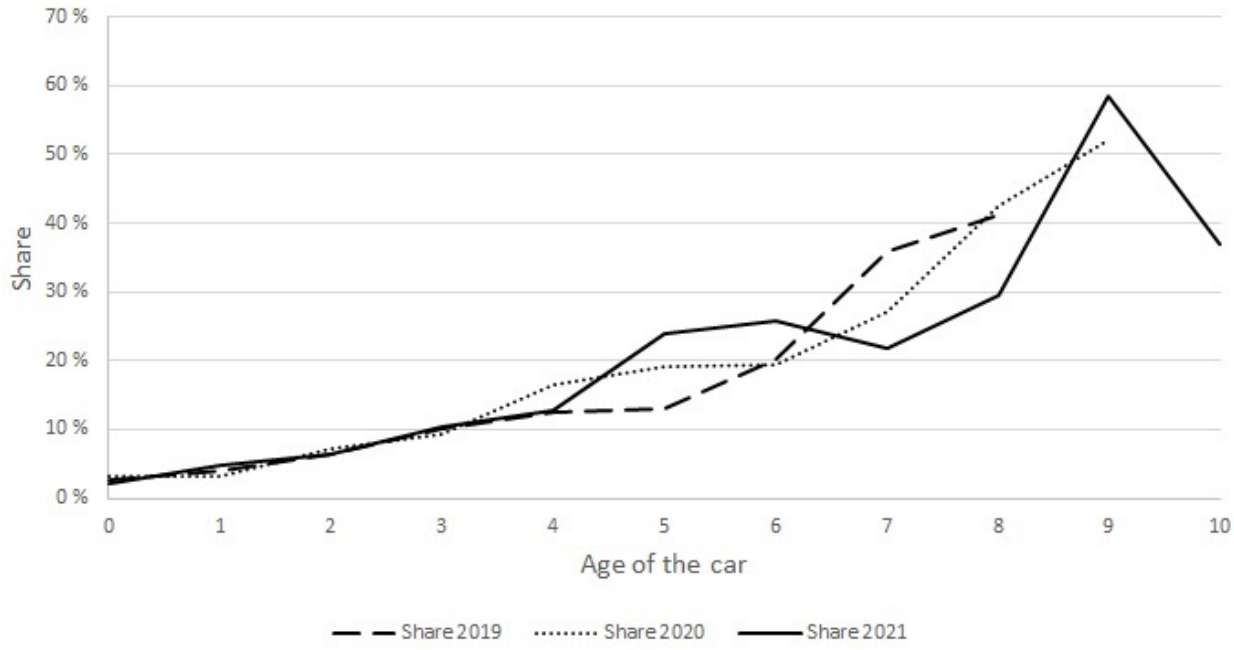
[16] Email correspondence with researchers at NTNU and SINTEF and phone conversation with a representative from a car recycle company (Bilgjenvinning AS), which has 45% of the car recycling market.

[17] 5 years for the Leafs between 2011 and 2015

[18] We have not looked into whether those that answer the survey are representative of electric vehicle owners in Norway.

[19] They were also asked the question in 2018, but in that round of the survey they don't report the year the car was new so we do not know the age of the car.

Figure 8: Reported battery degradation by vehicle age



Notes: The figure shows the fraction of respondents who report that they experience that the battery has degraded (score 1 or 2 out of 5) since the car was new.

the battery, the cars with short range might have more degraded batteries and as the battery technology improves, battery degradation might also reduce.

5.4.2 Maintenance cost

Gasoline vehicles typically have higher maintenance cost when they are older. Besides the battery degradation, this is not the case for electric vehicles, though.[20] Therefore, without technological change and battery degradation, electric vehicles should have a *higher* price on the secondhand car than gasoline vehicles if the two technologies are otherwise equal.

5.4.3 Supply side constraints

There have been – and still are – supply side constrains on electric vehicles, both that the models that fit the preferences of different consumers are not available and that there are waiting lists on popular electric vehicles. The number of individuals on the waiting list that actually end up buying the car when given the possibility is not public information. The waiting lists might also be part of a marketing strategy, as simply raising the price on the car would seem to be a more straightforward approach. We don't know if and how the supply side constrains affect the secondhand car market, but we can assume that it had a positive effect on the price in the secondhand electric car market. Hyundai Kona, for instance, has been advertised with higher price on finn.no than the price on the new vehicle, but we do not know whether the vehicle is sold for this price. If waiting lists have influenced the used car market, the effect is probably

[20]See for instance Green Cars (2021).

that the price fall on electric vehicles is lower than without the waiting lists. This means that without supply side constraints the price fall on electric vehicles would probably be higher, especially on large electric vehicles.

5.5 Robustness

We check whether the main results hold under other specifications than in Table 3. The difference in price fall between gasoline and electric vehicles is statistically significant in all robustness checks. We use all variables available, such as transmission, wheel drive and main color. In addition, instead of using the price when the vehicle was new as control, we use the new car price the year the vehicle was sold used. Especially for electric vehicles the price of new vehicles might change in a non-linear way because of new models entering the market and reducing prices on existing models (The Norwegian Electric Vehicle Association, 2021b). The price fall difference when we do not control for dealer fixed effects and at the same time control for new vehicle price when the vehicle was sold is very high (Table A-20, column 5), indicating that the private sale of electric vehicles and gasoline vehicles is different. We also test whether the main results hold when we drop the observations that are 0 years old when they are sold on finn.no. We also take out the dummies on those that miss the control variables new vehicle price and mileage (which result in a smaller sample). In addition we do the regression with absolute values, instead of log values. We also show the results when clustering the standard errors differently, both with make $\times$ fuel and make $\times$ the year the vehicle is new. The standard errors are as expected somewhat smaller with more clusters, but the statistical significance stay at the same level. The robustness checks are reassuring for the main result. See more details in Appendix E.

6 Conclusion

In this article we have investigated whether the price of electric vehicles decline faster than the price of gasoline vehicles. We have found empirical evidence that they do, but only those with range below 200 km. Our hypothesis is that the faster price fall on electric vehicles compared to gasoline vehicles is mostly due to faster technological development. As the adoption of electric vehicles is increasing, this is relevant information for more consumers in more markets. The valuation of electric vehicles that are ten years or younger in 2021 is a snapshot that might change as the improvements of the technology of electric vehicles flattens out. Comparing the results of this analysis with an analysis that is done 2-10 years later will be interesting. It will especially be interesting to see how the price path of the electric vehicles with longer range than 200 km develops. As the electric vehicles with range from 200 km and upwards is still young, we need to wait some more years to get the full picture of the price path of electric vehicles with longer range. Further, the price path of other technologies with rapid improvements would be interesting to investigate.

Our findings do not directly answer whether buying an electric vehicle is an economic sensible choice. Even if electric vehicles with less range than 200 km have fallen more in price the last decade than gasoline vehicles, there are other factors than value loss that influence the total cost of ownership of a vehicle. Electric vehicles have lower maintenance cost and lower fuel cost compared to vehicles with internal combustion engine. The batteries can be reused for other purposes and the car can be recycled (Kelleher Environmental, 2019). In addition, electric vehicles are subsidized in many countries, making new technology cheaper for consumers (IEA, 2021).

This paper is an investigation into how the price path of different technologies develops over the life-time of the car. We have looked into some heterogeneities related to range, price and size. It could be interesting to investigate further which factors influence the vehicle price and the price fall, for instance using causal forest approaches.

References

Acemoglu, D., Aghion, P., Bursztyn, L., & Hemous, D. (2012). The environment and directed technical change. *American Economic Review*, *102*(1), 131–66.

Adda, J., & Cooper, R. (2000). Balladurette and Juppette: A Discrete Analysis of Scrapping Subsidies. *Journal of Political Economy*, *108*(4), 778–806.

Aghion, P., & Howitt, P. W. (1998). *Endogenous growth theory*. MIT press.

Akerlof, G. A. (1970). The market for "lemons": Quality uncertainty and the market mechanism. *The Quarterly Journal of Economics*, *84*(3), 488–500.

Archsmith, J., Muehlegger, E., & Rapson, D. S. (2022). Future Paths of Electric Vehicle Adoption in the United States: Predictable Determinants, Obstacles, and Opportunities. *Environmental and Energy Policy and the Economy*, *3*(1), 71–110.

Balcer, Y., & Lippman, S. A. (1984). Technological expectations and adoption of improved technology. *Journal of Economic Theory*, *34*(2), 292–318.

Barrett, S. (2009). The coming global climate-technology revolution. *Journal of Economic Perspectives*, *23*(2), 53–75.

Berry, S., Levinsohn, J., & Pakes, A. (1995). Automobile prices in market equilibrium. *Econometrica*, 841–890.

Bloomberg. (2020). Batteries for electric cars speed toward a tipping point. https://www.bloomberg.com/news/articles/2020-12-16/electric-cars-are-about-to-be-as-cheap-as-gas-powered-models

Bloomberg. (2021a). Battery price declines slow down in latest pricing survey. https://www.bloomberg.com/news/articles/2021-11-30/battery-price-declines-slow-down-in-latest-pricing-survey

Bloomberg. (2021b). EV battery prices risk reversing downward trend as metals surge. https://www.bloomberg.com/news/newsletters/2021-09-14/ev-battery-prices-risk-reversing-downward-trend-as-metals-surge

Bond, E. W. (1982). A direct test of the "Lemons" model: The market for used pickup trucks. *The American Economic Review*, *72*(4), 836–840.

Bond, E. W. (1983). Trade in used equipment with heterogeneous firms. *Journal of Political Economy*, *91*(4), 688–705.

Brückmann, G., Wicki, M., & Bernauer, T. (2021). Is resale anxiety an obstacle to electric vehicle adoption? results from a survey experiment in switzerland. *Environmental Research Letters*, *16*(12), 124027.

Chen, C.-W., Hu, W.-M., & Knittel, C. R. (2021). Subsidizing Fuel-Efficient Cars: Evidence from China's Automobile Industry. *American Economic Journal: Economic Policy*, *13*(4), 152–84.

Chen, J., Esteban, S., & Shum, M. (2013). When do secondary markets harm firms? *American Economic Review*, *103*(7), 2911–34.

Commission of the European Communities. (1999). Case No COMP/M.1406 - HYUNDAI / KIA. https://ec.europa.eu/competition/mergers/cases/decisions/m1406_en.pdf

Copeland, A., Dunn, W., & Hall, G. (2011). Inventories and the automobile market. *The RAND Journal of Economics*, *42*(1), 121–149.

Danielis, R., Scorrano, M., Giansoldati, M., & Rotaris, L. (2019). *A meta-analysis of the importance of the driving range in consumers' preference studies for battery electric vehicles* (Working Papers 19_2). SIET Società Italiana di Economia dei Trasporti e della Logistica.

De Groote, O., & Verboven, F. (2019). Subsidies and time discounting in new technology adoption: Evidence from solar photovoltaic systems. *American Economic Review*, *109*(6), 2137–72.

Dhakal, S., Minx, J., F.L. Toth, A. A.-A., Meza, M. F., Hubacek, K., Jonckheere, I., Kim, Y.-G., Nemet, G., Pachauri, S., Tan, X., & Wiedmann, T. (2022). Emissions Trends and Drivers. In P. Shukla, J. Skea, R. Slade, A. A. Khourdajie, R. van Diemen, D. McCollum, M. Pathak, S. Some, P. Vyas, R. Fradera, M. Belkacemi, A. Hasija, G. Lisboa, S. Luz, & J. Malley (Eds.), *IPCC, 2022: Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, UK; New York, NY, USA.

Esteban, S., & Shum, M. (2007). Durable-goods oligopoly with secondary markets: The case of automobiles. *The RAND Journal of Economics*, *38*(2), 332–354.

European Commission. (2018). In-depth analysis in support of the commission communication com(2018) 773. A Clean Planet for all. https://ec.europa.eu/clima/system/files/2018-11/com_2018_733_analysis_in_support_en.pdf

Evyon. (2022). Planet-friendly battery energy storage systems. https://www.evyon.com/

Fudenberg, D., & Tirole, J. (1998). Upgrades, tradeins, and buybacks. *The RAND Journal of Economics*, 235–258.

fueleconomy.gov. (n.d.). Frequently Asked Questions. https://www.fueleconomy.gov/feg/info.shtml%5C#sizeclasses

Gavazza, A., Lizzeri, A., & Roketskiy, N. (2014). A quantitative analysis of the used-car market. *American Economic Review*, *104*(11), 3668–3700.

Gillingham, K., Iskhakov, F., Munk-Nielsen, A., Rust, J. P., & Schjerning, B. (2022). Equilibrium trade in automobiles. *Journal of Political Economy*.

Glerum, A., Stankovikj, L., Thémans, M., & Bierlaire, M. (2014). Forecasting the demand for electric vehicles: Accounting for attitudes and perceptions. *Transportation Science*, *48*(4), 483–499.

Gordon, B. R. (2009). A dynamic model of consumer replacement cycles in the PC processor industry. *Marketing Science*, *28*(5), 846–867.

Gowrisankaran, G., & Rysman, M. (2012). Dynamics of consumer demand for new durable goods. *Journal of Political Economy*, *120*(6), 1173–1219.

Green Cars. (2021). Cost to maintain an electric car. https://www.greencars.com/post/what-does-it-cost-to-maintain-an-electric-car

Guan, J. (2021). Automobile Replacement and Government Subsidy: An Analysis of the CARS Program. *Available at SSRN 3873076*.

Holland, S. P., Mansur, E. T., & Yates, A. J. (2021). The electric vehicle transition and the economics of banning gasoline vehicles. *American Economic Journal: Economic Policy*, *13*(3), 316–44.

IEA. (2021). Global EV Outlook 2021. https://www.iea.org/reports/global-ev-outlook-2021

IEA. (2022). Global EV Outlook 2022. https://www.iea.org/reports/global-ev-outlook-2022

IIHS and HLDI. (2020). HLDI automobile size and class definitions. https://www.iihs.org/media/b19c7e8c-54ea-4a35-a3bb-3a05fa2a5c16/g5MZTA/Ratings/Protocols/current/hdi-auto-size-class.pdf

Ishihara, M., & Ching, A. T. (2019). Dynamic demand for new and used durable goods without physical depreciation: The case of Japanese video games. *Marketing Science*, *38*(3), 392–416.

J.D. Power. (2020). Electric Vehicle Range Testing: Understanding NEDC vs. WLTP vs. EPA. https://www.jdpower.com/Cars/Shopping-Guides/electric-vehicle-range-testing-understanding-nedc-vs-wltp-vs-epa

J.P. Morgan. (2018). Driving into 2025: The future of electric vehicles. https://www.jpmorgan.com/insights/research/electric-vehicles

J.P. Morgan. (2020). The future is electric. https://www.jpmorgan.com/insights/research/future-is-electric

Kelleher Environmental. (2019). Research study on reuse and recycling of batteries employed in electric vehicles: The technical, environmental, economic, energy and cost implications of reusing and recycling ev batteries.

Li, S., Liu, Y., & Wei, C. (2020). *The cost of greening stimulus: A dynamic discrete choice analysis of vehicle scrappage programs* [Mimeo, GWU].

Liu, Y., & Cirillo, C. (2017). A generalized dynamic discrete choice model for green vehicle adoption. *Transportation research procedia*, *23*, 868–886.

Mian, A., & Sufi, A. (2012). The effects of fiscal stimulus: Evidence from the 2009 cash for clunkers program. *The Quarterly Journal of Economics*, *127*(3), 1107–1142.

National Highway Traffic Safety Administration. (n.d.). Frequently Asked Questions. https://www.nhtsa.gov/ratings

Norwegian Ministry of Transport and Communications. (2017). National Transport Plan 2018–2029. Meld. St. 33 (2016–2017) Report to the Parliament (Stortinget) (white paper). English summary.

Pathak, M., Slade, R., Shukla, P., Skea, J., Pichs-Madruga, R., & Ürge-Vorsatz, D. (2022). Technical Summary. In P. Shukla, J. Skea, R. Slade, A. A. Khourdajie, R. van Diemen, D. McCollum, M. Pathak, S. Some, P. Vyas, R. Fradera, M. Belkacemi, A. Hasija, G. Lisboa, S. Luz, & J. Malley (Eds.), *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, UK; New York, NY, USA.

Porter, R. H., & Sattler, P. (1999). *Patterns of trade in the market for used durables: Theory and evidence* (NBER Working Paper No. 7149).

Purohit, D. (1992). Exploring the relationship between the markets for new and used durable goods: The case of automobiles. *Marketing Science*, *11*(2), 154–167.

Rosenberg, N. (1976). On technological expectations. *The Economic Journal*, *86*(343), 523–535.

Rust, J. (1987). Optimal replacement of GMC bus engines: An empirical model of Harold Zurcher. *Econometrica*, 999–1033.

Sallee, J. M., West, S. E., & Fan, W. (2016). Do consumers recognize the value of fuel economy? evidence from used car prices and gasoline price fluctuations. *Journal of Public Economics*, *135*, 61–73.

Schiraldi, P. (2011). Automobile replacement: A dynamic structural approach. *The RAND journal of economics*, *42*(2), 266–291.

Solow, R. M., Tobin, J., von Weizsäcker, C. C., & Yaari, M. (1966). Neoclassical Growth with Fixed Factor Proportions. *Review of Economic Studies*, *33*(2), 79–115.

Springel, K. (2021). Network externality and subsidy structure in two-sided markets: Evidence from electric vehicle incentives. *American Economic Journal: Economic Policy*.

Stock, J. H. (2020). Climate change, climate policy, and economic growth. *NBER Macroeconomics Annual*, *34*(1), 399–419.

Stolyarov, D. (2002). Turnover of used durables in a stationary equilibrium: Are older goods traded more? *Journal of Political Economy*, *110*(6), 1390–1413.

Strittmatter, A., & Lechner, M. (2020). Sorting in the used-car market after the Volkswagen emission scandal. *Journal of Environmental Economics and Management*, *101*, 102305.

The Norwegian Electric Vehicle Association. (2021a). Bruktbil-bonanza: Nå topper elbilene blant to år gamle biler. https://elbil.no/na-topper-elbilene-blant-to-ar-gamle-biler/

The Norwegian Electric Vehicle Association. (2021b). Prisene presses: Nå kan du gjøre et elbilkupp. https://elbil.no/prisene-presses-na-kan-du-gjore-et-elbil-kupp/

The Norwegian Electric Vehicle Association. (2022a). The electric vehicle selector. https://elbilvelgeren.elbil.no/

The Norwegian Electric Vehicle Association. (2022b). Nybilsalget 2021: Nå selges det flere elbiler enn dieselbiler i Europa. https://elbil.no/na-selges-det-flere-elbiler-enn-dieselbiler-i-europa/

The Norwegian Tax Administration. (n.d.). Calculating the one-off registration tax for plug-in hybrids. https://www.skatteetaten.no/en/person/duties/cars-and-other-vehicles/importing/which-duties-do-you-have-to-pay/one-off-registration-tax/what-is-the-one-off-registration-tax/calculating-the-one-off-registration-tax-for-plug-in-hybrids/

Waldman, M. (2003). Durable goods theory for real world markets. *Journal of Economic Perspectives*, *17*(1), 131–154.

Wykoff, F. C. (1970). Capital depreciation in the postwar period: Automobiles. *The Review of Economics and Statistics*, 168–172.

Appendix

A The effect of technological progress

A.1 Opting out of car ownership

In the main analysis we assume that all consumers need a car, hence implicitly that the utility of not owning a car is sufficiently low. In many settings, other means of transportation can be a suitable alternative. To include this in the model, we can introduce an outside opportunity of not owning a car yielding a utility level $\underline{U}$. This alternative is most relevant for consumers with a low car preference parameter h. Hence this alternative is chosen for consumers with $U^O < \underline{U}$. This yields a new cut-off level $\underline{h}$ defined by

$$x_u\underline{h} - p_u + \beta(x_u\underline{h} - p_u) = \underline{U} \Rightarrow \underline{h} = \frac{\underline{U}}{(1+\beta)x_u} + \frac{p_u}{x_u}$$

As the number in the N and O groups still have to be equally sized in equilibrium, this yields a new equilibrium condition

$$F\left(\frac{p_n - (1+\beta)p_u}{(1-\mu)x_n}\right) - F\left(\frac{\underline{U}}{(1+\beta)x_u} + \frac{p_u}{x_u}\right) = 1 - F\left(\frac{p_n - p_u}{(1-\mu)x_n}\right)$$

This change to the model does not change any qualitative insights from the model, so to maintain simplicity we disregard the presence of an outside opportunity for the rest of the paper.

A.2 Proof of theoretical results

To see the effect of technological progress on the market, we can differentiate equation (8) to get

$$f(\underline{h})\left[-\frac{1+\beta}{\left(1-\frac{\mu}{\gamma}\right)x_n}dp_1 - \frac{[p_n-(1+\beta)p_u]\frac{\mu x_n}{(\gamma)^2}}{\left[\left(1-\frac{\mu}{\gamma}\right)x_n\right]^2}d\gamma\right] = -f(\bar{h})\left[-\frac{1}{(\gamma-\mu)x_n}dp_1 - \frac{(p_n-p_u)x_n}{[(\gamma-\mu)x_n]^2}d\gamma\right] \quad (13)$$

where the left hand side are the demand effects and the right hand side the supply effects. Solving, we find

$$\frac{dp_1}{d\gamma} = -x_0\frac{f(\underline{h})\underline{h}\frac{\frac{\mu}{(1+\gamma)^2}}{1-\frac{\mu}{\gamma}} + f(\bar{h})\bar{h}\frac{1}{(\gamma-\mu)}}{f(\underline{h})\frac{1+\beta}{1-\frac{\mu}{\gamma}} + f(\bar{h})\frac{1}{\gamma-\mu}} \quad (14)$$

$$= -x_0\frac{f(\underline{h})\underline{h}\frac{\mu}{\gamma} + f(\bar{h})\bar{h}}{f(\underline{h})(1+\beta)(\gamma) + f(\bar{h})} < 0 \quad (15)$$

Moreover, we have

$$\frac{d\bar{h}}{d\gamma} = -\frac{(p_n - p_u)x_n}{(\gamma - \mu)^2 x_n^2} - \frac{1}{(\gamma - \mu)x_n}\frac{dp_u}{d\gamma}$$

Using equation (8), we find

$$\begin{aligned}\frac{d\bar{h}}{d\gamma} &= -\frac{1}{(\gamma - \mu)}\left(\bar{h} - \frac{f(\underline{h})\underline{h}\frac{\mu}{\gamma} + f(\bar{h})\bar{h}}{f(\underline{h})(1+\beta)\gamma + f(\bar{h})}\right) \\ &= -\frac{f(\underline{h})}{(\gamma - \mu)} \times \frac{(1+\beta)\gamma\bar{h} - \frac{\mu}{\gamma}\underline{h}}{f(\underline{h})(1+\beta)\gamma + f(\bar{h})}\end{aligned}$$

As $(1+\beta)\gamma\bar{h} > \frac{\mu}{\gamma}\underline{h}$, we then get $\frac{d\bar{h}}{d\gamma} < 0$.

B Data

In this Appendix, we present details of the data we use in our analysis.

B.1 Variables from finn.no

The data from finn.no forms the basis of our analysis. It includes a hashed vehicle id number, chassis number, the listed secondhand price of the vehicle the seller wants, the year the vehicle is first registered, year model, fuel type, mileage, make and model, number of seats, municipality of the seller, dealer type, engine effect, engine volume, transmission, wheel drive, main color, as well as the month and year of an ad on finn.no.

We will now go through the variables that we use in the analysis.

B.1.1 Vehicle id number

Each vehicle has an id number which is unique and encrypted to keep the data anonymous. We combine this variable with the chassis number, dealer type, effect, engine volume, fuel, main color, make, model, municipality of the seller, transmission wheel drive, year model, the year the vehicle is first registered and number of seats to check whether a vehicle has been advertised for more than a month (and therefore becomes a duplicate observation) and to a lower price.

B.1.2 Vehicle age

To find the age of a vehicle, we can use two variables to tell us the year the vehicle was new: The year model and the year the vehicle was first registered. The year model in itself is an imprecise term. Some manufacturers start selling year model t early in year $t-1$, and some maintain the year on the model until they change the model.

However, year of first registration can also be wrong. Although our data ends in 2021, there are observations with year of first registration date after 2021. There are also numerous observations with year of first registration before 1940. Although some of these may be antique cars, some are clear mistakes. There are for instance multiple Nissan Leaf presumably registered before 1940, which is unreasonable as the model entered the market after 2010.

Our solution is to use the lowest of the year of first registration and the model year whenever both are present. Moreover, we assume that vehicles first registered before 1940 is a mistake, and in this case we use the year model unless the year of first registration and year model is the same year, we keep the year of first registration.

As we have data on the year the vehicle is advertised on finn.no, we find the age of the vehicle by subtracting the year the vehicle is advertised with the year the vehicle is new.

B.1.3 Fuel type

The data from finn.no has data on fuel type. However, there may be mistakes by the seller, for instance claiming that a vehicle is a gasoline vehicle when it is a hybrid gasoline vehicle or stating that it is an electric vehicle when it is a hybrid or plug-in hybrid. When there is only one observation of a vehicle model one year that is electric, the electric model is not listed by OFV, and we do not recognize the model name as an electric vehicle (there are so few electric vehicle models that it is possible to know most of them), we take them out of the analysis, because it is likely that they are erroneously classified as electric vehicles. This is the case of 41 observations.

Gasoline vehicles that are not found on the OFV list are treated differently, see more elaboration on this in Section B.2.1.

The finn data do not distinguish between plug-in hybrid and hybrid. To distinguish between the two, we also use data from OFV. If a vehicle is listed as gasoline-hybrid in the finn data and plug-in gasoline hybrid or a gasoline vehicle in the OFV data, we code it as a plug-in gasoline hybrid. If a vehicle is listed as hybrid in the finn data and hybrid *and* plug-in hybrid in the OFV data, we do not change it. As most of our analyses compare electric and gasoline vehicles this coding scheme has a minor impact on our results. In Table A-18, however, we compare all fuel types.

B.1.4 The price of the secondhand vehicle

We only have the price the seller lists on the finn platform, not the price the vehicle is actually sold at. There can be case where buyer and seller agree on a lower price than the listed one.

Moreover, the price is without re-registration fee which varies through the period of investigation and for different vehicles, depending on age and fuel.

B.1.5 Mileage

We use mileage as a control variable because this is a variable that probably affect the price of the vehicle. Finn has rounded the number to the nearest thousand in order to anonymize the data. Observations where mileage is missing are controlled for with a dummy variable. See Table A-2 to see the number of missing on mileage.

B.1.6 Number of seats

This variable is used to distinguish between passenger vehicles and utility vehicles with the same model name.

B.2 Variables from OFV

The Norwegian Road Federation (OFV) data are merged into the finn data set by fuel, model, make and the year the vehicle is new. The variables from OFV that we use are the price on the new vehicle and body style category.

The data from OFV are combined with the data from finn.no matching on the following variables: make, model, fuel and the year the vehicle is new.

B.2.1 Price on the new vehicle

Norwegian Road Federation (OFV) collects prices on new vehicles from all importers that are formally linked to the producer. The price list of June every year is used to find the price on the new vehicle. When not found in the June list, we use the November list or the December list. If not found on either June, November or December list, the vehicle is marked as missing price on the new vehicle (see below for more information on the reason for the vehicle missing on the price list). See Table A-2 to see the number of missing on new vehicle price.

There are many different equipment level within the same model and the information from finn.no do not tell us which equipment level each vehicle has. Some equipment levels within a model are a lot more expensive than the others. Therefore, we take the median price of the make, model, fuel and year. For robustness check we take out those models where the ratio between the maximum price and the minimum price is above 1.5. This can be seen in Table 3, column 4.

Body style category should also be one of the variables that the median price is based on, but since finn.no do not have this variable, we can not merge on this variable. Some models are more than one type of category. For instance Ford Focus can be bought as a hatchback or station wagon. Mercedes-Benz A-class is either sedan or hatchback. Mercedes-Benz C-class is either sedan or station wagon. Then the median price is the median of all the models in the two types of vehicles body style categories.

Notice that the new prices we use are listed new prices. Actual prices of new cars could be lower due to e.g. haggling, rebates or campaigns.

Those observations with make or model "others" or "N/A" and fuel "N/A" when the model can be both electric and conventional vehicle are not merged and therefore lack the price on the new vehicle.

Some observations on finn.no are not found on the OFV list of new vehicle prices. There are four main explanations: 1) privately imported new vehicles from the factory, i.e. not through the importer that is related to the producer, 2) models from earlier years, 3) import of used vehicles, and 4) mistakes in the OFV list or at finn.no, for instance the advertiser is not aware that the vehicle is a hybrid and list it as a gasoline vehicle.

An example of explanation 1) is Fiat 500 Plug-in Hybrid which was produced for the American market. Fiat decided not to sell these vehicles in Europe, but some were imported through channels that were not related to the producer's importer network.

The price on the new vehicle in category 2) is difficult to know. We can find the price on the model in earlier years, but the price probably changes from year to year.

For category 1), the price on finn.no is strictly speaking the price of the new vehicle in the Norwegian market if the car is 0 years-old. All vehicles that are not part of the OFV list get a dummy and the dummy is controlled for in the regression in Table 3. We also have the same specifications as in Table 3 without a dummy on those missing new vehicle price and that can be seen in Table A-23.

B.2.2 OFV listed fuel type

In the beginning of the period of investigation there were some models that were flexible fuel vehicles (cars that are able to use both gasoline and ethanol). OFV have them on their list, but as the market for these vehicles never took off in Norway, finn.no do not distinguish between gasoline vehicles and flexible fuel vehicles. We define all flexible fuel vehicles in OFV data as gasoline vehicles.

B.2.3 Size categories

There is no clear definition of different size categories. The EU Commission lists different segments in the car market, but also state that "the exact market definition was left open"(Commission of the European Communities, 1999, p.2).

In the USA the Environmental Protection Agency (EPA) has different size classes based on body style combined with passenger and cargo volume (fueleconomy.gov, n.d.). In contrast, the National Highway Traffic Safety Administration (NHTSA) in the USA categorize by class and weight (National Highway Traffic Safety Administration, n.d.). A third option in the USA is by The Insurance Institute for Highway Safety (IIHS) and The Highway Loss Data Institute (HLDS) which both are organizations funded by auto insurers and insurance associations. They use a combination of weight and length times width (IIHS and HLDI, 2020).

Body style Most models have different variants. Some models are in two different body style categories. For instance, Volkswagen Golf can be both a hatchback or a station wagon. However, for electric vehicles the different variants of a model are mostly in the same body style categories. For gasoline there are several models that can be both a hatchback and a station wagon. We categorize them based on which body style categories there are most model variants of.

We use the body style categories that The Norwegian Road Federation (OFV) categorize dif-

ferent models into.[21] We have translated their definition.

"*Cabriolet* are cars with roofs that can be opened or removed, either by folding it into the body style, or being completely removed. Roadsters should have body style category cabriolet.

Hatchbacks are cars with a large tailgate/rear door that include the rear window. The rear edge of the rear window ends where the body ends, without any horizontal surface/trunk lid. The hedge on the hatchback may have different inclination. The trunk is relatively small compared to the total volume of the car. The station wagon has larger volume, while the body shape may otherwise be quite similar.

Coupes are cars that have prioritized appearance at the expense of space and practical considerations. They are characterized by what most people will perceive as "elegant lines". Often, the coupes are lower with a flatter rear window than ordinary hatchbacks and sedans, which the space, especially from the front seats and backwards, suffers underneath. The tailgate is hinged under the rear window. Coupes can have 2 and 4 doors.

Pickups are cars with an open loading plane behind a cab. The cab can contain several rows of seats.

Sedan are cars with preferably 4 doors and separate trunk and marked trunk lid that are hinged under/behind the rear window.

Station wagon are cars with full height backwards to the tailgate. The tailgate can be somewhat sloping and the trunk is open towards the cabin. They are characterized by large trunk in relation to the total volume of the car.

Multipurpose car are cars that are designed for maximum interior space utilization and flexibility. The body style shape is similar to that of the station wagon or hatchback, but the multipurpose cars are usually higher than these, albeit with normal ground clearance. They have a minimum of 5 seats in addition to luggage space."

SUV is not defined by OFV.

Weight

Weight can be used as a proxy for size. We take the median of the different trims of the same model. As electric vehicles are heavier than gasoline vehicles due to the batteries, we use the gasoline vehicles as the basis to find the cutoff between large and small vehicles. We use the 75th percentile of the weight for all gasoline vehicles in the sample as the cutoff. This is 1375 kg. How much more an electric vehicle weigh due to the batteries is difficult to know, but the tax authorities use 15% extra weight for plug-in hybrids from 1st of January 2022 and before that they used 23% (The Norwegian Tax Administration, n.d.). We therefore add 10%, 20% and 30% to the electric vehicle weight when distinguishing between large and small vehicles

[21] Personal email communication with Kjell Magne Aalbergsjø in OFV, 11.02.22.

Table A-1: Observations not part of the analysis

	Number of observations
Ads on finn.no 2011- June 20th 2021	5 546 617
Duplicates	1 475 852
Older than 2011	2 715 036
Price over 2 mill NOK	8 977
Price under 10 000 NOK	1 703
Age -1 or less	6 363
Age missing	45
Advertised for more than a month without changing the price	167 106
Utility vehicles	1 975
Missing information, such as model name	2 054
Wrong fuel (see Section B.1.3 for explanation)	41
Think	109
Buddy	19
Hydrogen vehicles	66
Gas vehicles	139
Total number of observations (all fuels, except hydrogen and gas)	1 167 132
Total number of observations, electric and gasoline	452 743

based on weight in Table A-12.

B.3 Variables from other sources

B.3.1 Range

Range is taken from the webpage of the Norwegian Electric Vehicle Association (The Norwegian Electric Vehicle Association, 2022a). When the same model the same year has different range alternatives, we construct the median of the range. The range we use is the WLTP, which is the new standard. If the old standard, NEDC, is the only available, we reduce the driving range by a factor of 0.65 (J.D. Power, 2020). Some models are for sale with different year models with different range at the same time and therefore we do not know for sure the range of the car the year the vehicle is new. We use the median range of the year model the year the vehicle is new.

B.4 Sample selection

Vehicles that are new in 2011 or after is part of the analysis. We therefore do not include the observations for vehicles that are new earlier than 2011. See Table A-1 for an overview of the number of observations that are not part of the analysis.

We remove duplicate data entries based on a combination of the chassis number, dealer type, effect, engine volume, fuel, main color, make, model, municipality of the seller, transmission wheel drive, year model, the year the vehicle is first registered and number of seats. We use the ad that is newest in the main analysis.

In order to not let outliers influence the result, we analyze vehicles with a price range between

Table A-2: Number of observations with some of the variables missing

	Number of observations
Total	452 743
Missing new vehicle price	6 921
Missing body style	6 921
Missing mileage	17 160
Missing range (and electric vehicle)	452

10 000 NOK and 2 million NOK, see Table A-1 for the number of observations. In addition, we take out Think and Buddy brands as these can not be characterized as modern vehicles. Observations where the recorded vehicle age is negative at the time of transaction are also removed.

The average time to sell a car on finn.no is less than a month (The Norwegian Electric Vehicle Association, 2021a). If the car is advertised for more than a month and the price is not reduced from one month to the next, it is likely that the car is not sold at all. Therefore, observations that are duplicates and where the price do not change from one month to the next are taken out of the analysis.

C Descriptive data

Table A-3: Number of vehicles based on fuel

Number of vehicles		Share
Gasoline vehicles	295 350	25%
Electric vehicles	157 393	13%
Hybrid vehicles	66 072	6%
Plug-in hybrid vehicles	64 711	6%
Diesel vehicles	583 606	50%
Total	1 167 132	

Table A-4: Number of vehicles that are new in 2011 or later advertised each year.

Year sold	Gasoline	Electric
	Number of vehicles	
2011	1 632	53
2012	5 510	191
2013	10 645	898
2014	17 382	1 859
2015	23 850	4 338
2016	31 554	8 107
2017	40 830	15 848
2018	42 699	27 490
2019	49 486	33 981
2020	48 803	39 201
2021	22 959	25 427

Table A-5: Number of vehicles based on how old they when they are for sale

	Number of vehicles	
Age	Electric	Gasoline
0	23 045	22 461
1	31 647	41 611
2	26 813	41 977
3	26 677	58 919
4	19 788	41 762
5	13 308	30 347
6	8 559	22 559
7	4 345	16 932
8	2 107	11 177
9	854	5 890
10	250	1713
Mean age	2.67	3.50
Mean age for vehicles that are 5 years or younger	2.20	2.62

Table A-6: The mean range in the year the vehicles are new and sold in the secondhand market. The median refers to the price of the vehicle as new.

Year	Mean range new	Mean range sold	Mean range sold over the median	Mean range sold below the median
2011	114	108	–	108
2012	122	115	–	115
2013	178	134	300	121
2014	171	168	300	124
2015	167	178	304	128
2016	199	177	323	132
2017	263	188	346	149
2018	292	201	382	173
2019	390	244	429	194
2020	397	276	451	201
2021	406	294	450	216
For all years	240		418	183

We have calculated the statistics for new vehicle price weighted by the vehicles that are on finn.no..
The 50th percentile is 359 900 NOK.
In 2011 and 2012 there are no electric vehicles with price as new equal to or over the median.
Over median includes those equal to the median.

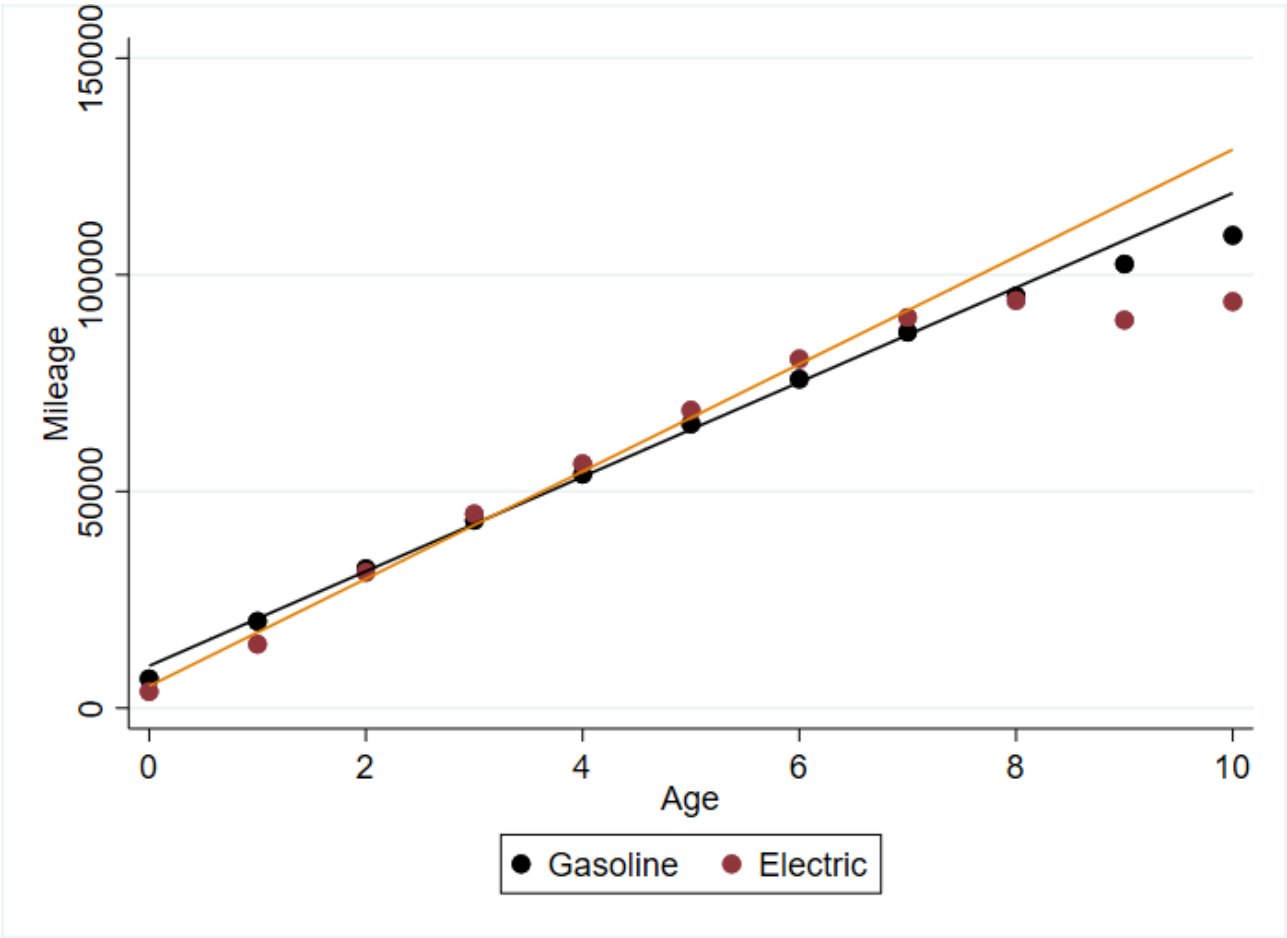
Table A-7: Share of vehicles based on seller.

	Share of vehicles	
	Electric	Gasoline
Private seller	46%	25%
Professional seller of the same make	22%	55%
Other professional seller	32%	20%

Table A-8: Top 10 secondhand models

	Electric secondhand		Gasoline secondhand	
	Model	Share	Model	Share
1	Nissan Leaf (Hatchback)	22%	VW Golf (Hatchback)	7%
2	VW E-golf (Hatchback)	15%	VW Polo (Hatchback)	4%
3	Tesla Model S (Hatchback)	12%	Ford Focus (Hatchback/Station wagon)	3%
4	BMW i3 (Hatchback)	9%	Ford Fiesta (Hatchback)	3%
5	Kia E-soul (Hatchback)	6%	Audi A3 (Hatchback)	3%
6	VW E-up! (Hatchback)	4%	Toyota Yaris (Hatchback)	2%
7	Tesla Model X (SUV)	3%	Mercedes A-klasse (Hatchback/Sedan)	2%
8	Renault Zoe (Hatchback)	3%	Toyota Avensis (Sedan/Station wagon)	2%
9	Hyundai Ioniq (Hatchback)	3%	Skoda Octavia (Station wagon)	2%
10	Tesla Model 3 (Sedan)	3%	Audi A1 (Hatchback)	2%

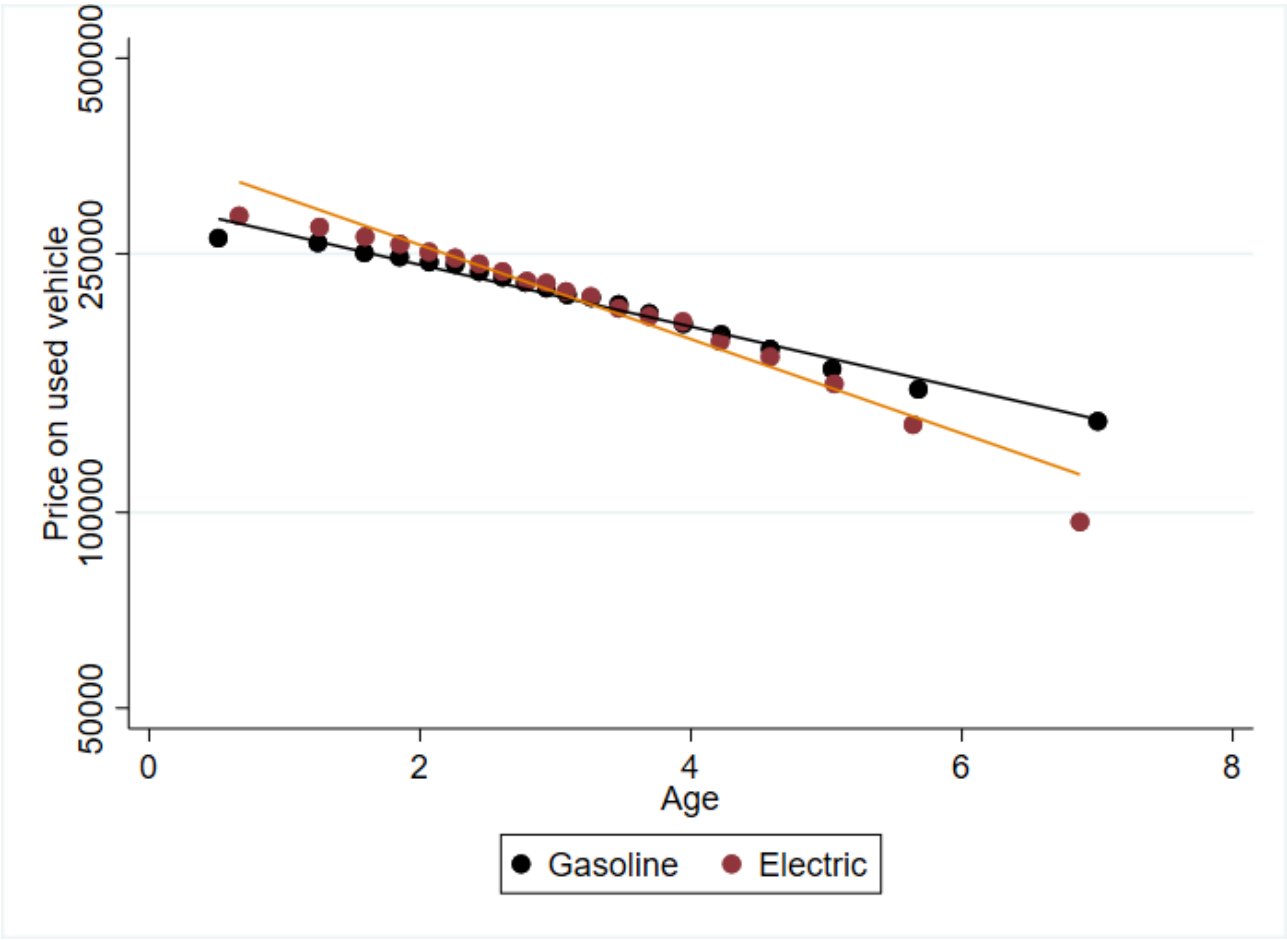
Figure A-1: Binned scatterplot of the relationship between mileage and age.



D More detailed results

The relationship between vehicle age and secondhand price is illustrated in Figure A-2. As expected, the price is declining in age. We also see that this decline is clearly stronger for electric vehicles than for gasoline cars.

Figure A-2: Secondhand vehicle prices by age and fuel type



Notes: Each point represent an equal number of observations. Results control for mileage, the log price of the new car and dummies for missing variables. The y axis is on a logarithmic scale.

Table A-9: Table 3 with age squared.

	(1)	(2)	(3)	(4)	(5)
Age	-0.0336	-0.0316	-0.0415	-0.0339	-0.0413
	(0.00680)	(0.00676)	(0.00664)	(0.00860)	(0.00652)
Age squared	-0.00804	-0.00807	-0.00764	-0.00863	-0.00793
	(0.000553)	(0.000567)	(0.000558)	(0.000661)	(0.000575)
Electric × Age	-0.0211	-0.0187	0.00536	0.00278	-0.00934
	(0.0216)	(0.0211)	(0.0168)	(0.0217)	(0.0215)
Electric × Age squared	-0.00602	-0.00626	-0.00709	-0.00830	-0.00680
	(0.00214)	(0.00214)	(0.00159)	(0.00181)	(0.00211)
Ln new price	1.083	1.063	1.016	1.111	1.076
	(0.0255)	(0.0308)	(0.0332)	(0.0327)	(0.0253)
Ln mileage × Gasoline	-0.102	-0.103	-0.0989	-0.0891	-0.102
	(0.00686)	(0.00583)	(0.00669)	(0.00484)	(0.00684)
Ln mileage × Electric	-0.0222	-0.0210	-0.0459	-0.0353	-0.0306
	(0.0136)	(0.0137)	(0.00638)	(0.0141)	(0.0136)
Year × fuel fixed effects	Y	Y	Y	Y	Y
Dealer fixed effects	Y	Y	Y	Y	N
Body style fixed effects	N	Y	N	N	N
Make fixed effects	N	N	Y	N	N
Taken out those with large variation in new vehicle price and those without new vehicle price	N	N	N	Y	N
Observations	452 743	452 743	452 743	283 785	452 743
R^2	0.865	0.867	0.884	0.909	0.863

Dependent variable is log of the secondhand price.

Standard errors clustered on make, in parentheses. There are 62 clusters in all but in (4) where there are 44 clusters.

Gasoline vehicles are the baseline. Year fixed effects are based on the year the vehicle is sold/advertised.

We use a dummy on those observations that have missing mileage and those that have missing new car price.

Table A-10: Table 3 without the electric vehicles with range below 200 km.

	(1)	(2)	(3)	(4)	(5)
Age	-0.108	-0.107	-0.110	-0.113	-0.115
	(0.00465)	(0.00433)	(0.00343)	(0.00573)	(0.00440)
Electric × Age	0.0322	0.0442	0.0370	0.0366	0.0397
	(0.00739)	(0.00851)	(0.00541)	(0.00798)	(0.00754)
Ln new price	1.056	1.006	1.041	1.089	1.050
	(0.0215)	(0.0267)	(0.0256)	(0.0227)	(0.0226)
Ln mileage × Gasoline	-0.0735	-0.0738	-0.0748	-0.0608	-0.0745
	(0.00735)	(0.00589)	(0.00675)	(0.00572)	(0.00738)
Ln mileage × Electric	-0.0404	-0.0422	-0.0372	-0.0266	-0.0478
	(0.00959)	(0.00966)	(0.00770)	(0.00575)	(0.00868)
Year × fuel fixed effects	Y	Y	Y	Y	Y
Dealer category fixed effects	Y	Y	Y	Y	N
Body style category fixed effects	N	Y	N	N	N
Make fixed effects	N	N	Y	N	N
Taken out those with large variation in new vehicle price and those without new vehicle price	N	N	N	Y	N
Observations	364 118	364 118	364 118	198 228	364 118
R^2	0.871	0.874	0.884	0.916	0.868

Dependent variable is ln of the secondhand price.

Standard errors clustered on make, in parentheses. There are 59 clusters in all but specification (4), where there are 44 clusters.

Gasoline vehicles are the baseline. Year fixed effects are based on the year the vehicle is sold/advertised.

We use a dummy on those observations that have missing mileage and those that have missing new car price.

Table A-11: Quantile regression

	(1) 25th percentile	(2) Median	(3) 75th percentile	(4) 90th percentile
Age	-0.113	-0.106	-0.0979	-0.0972
	(0.000388)	(0.000326)	(0.000348)	(0.000470)
Electric × Age	-0.0634	-0.0430	-0.0248	-0.0138
	(0.000699)	(0.000618)	(0.000557)	(0.000648)
Ln new price	1.039	1.066	1.095	1.115
	(0.00105)	(0.000902)	(0.000890)	(0.00117)
Ln mileage × Gasoline	-0.0679	-0.0625	-0.0626	-0.0632
	(0.000694)	(0.000579)	(0.000617)	(0.000901)
Ln mileage × Electric	0.0146	0.00433	-0.00895	-0.0209
	(0.000853)	(0.000732)	(0.000732)	(0.000830)
Year × fuel fixed effects	Y	Y	Y	Y
Dealer category fixed effects	Y	Y	Y	Y
Observations	452 743	452 743	452 743	452 743

Dependent variable is ln of the secondhand price.

Standard errors are robust, in parentheses.

Gasoline vehicles are the baseline. Year fixed effects are based on the year the vehicle is sold/advertised.

We use a dummy on those observations that have missing new vehicle price and mileage.

Table A-12: Different size categories based on either body style or weight.

	(1) Body style	(2) Weight 20% added	(3) Weight 10% added	(4) Weight 30% added
Age	-0.110	-0.115	-0.113	-0.115
	(0.00431)	(0.00425)	(0.00413)	(0.00425)
Electric × Age	-0.0574	-0.0560	-0.0607	-0.0561
	(0.0196)	(0.0172)	(0.0218)	(0.0170)
Large vehicles × Age	0.00463	0.0103	0.00954	0.0103
	(0.00384)	(0.00462)	(0.00473)	(0.00461)
Electric × Large vehicles × Age	0.0168	0.0526	0.0144	0.0553
	(0.0170)	(0.0129)	(0.0223)	(0.0137)
Ln new price	1.066	1.034	1.066	1.033
	(0.0265)	(0.0251)	(0.0242)	(0.0263)
Ln mileage × Gasoline	-0.0771	-0.0731	-0.0741	-0.0730
	(0.00645)	(0.00708)	(0.00703)	(0.00706)
Ln mileage × Electric	0.0104	-0.00441	0.00819	-0.00432
	(0.0110)	(0.00955)	(0.00979)	(0.0102)
Year × fuel fixed effects	Y	Y	Y	Y
Dealer fixed effects	Y	Y	Y	Y
Body style fixed effects	Y	Y	Y	Y
Observations	452 743	452 743	452 743	452 743
R^2	0.870	0.872	0.869	0.872

The cutoff between small and large vehicles based on weight is the 75th percentile for weight for gasoline vehicles. See Appendix B.2.3 for more information.

Weight added means how much more weight is added to the electric vehicles to be in the same category as gasoline vehicles.

Due to battery weight, electric vehicles have added 20% to the cutoff in column 2, 10% added in column 3 and 30% added in column 4.

Dependent variable is ln of the secondhand price.

Standard errors clustered on make, in parentheses. There are 62 clusters.

Small gasoline vehicles are the baseline. Year fixed effects are based on the year the vehicle is sold/advertised.

Large vehicles are defined as station wagon, SUV, pick-up and multi-purpose cars.

Small vehicles are sedan, hatchback, coupe and cabriolet.

We use a dummy on those observations that have missing new vehicle price and mileage.

Table A-13: Investigating vintage effects.

	(1)	(2)	(3)	(4)
Age	-0.0674	-0.0676	-0.0742	-0.0750
	(0.00475)	(0.00538)	(0.00510)	(0.00520)
Electric × Age	-0.0477	-0.0587	-0.0309	-0.0385
	(0.0131)	(0.0140)	(0.0104)	(0.0102)
Early × Age	-0.0317	-0.0518	-0.0272	-0.0472
	(0.00581)	(0.00495)	(0.00534)	(0.00458)
Early × Electric × Age	-0.0307	-0.0340	-0.0337	-0.0383
	(0.0151)	(0.0176)	(0.0132)	(0.0150)
Ln new price	1.064	1.081	1.012	1.015
	(0.0212)	(0.0254)	(0.0315)	(0.0328)
Ln mileage × Gasoline	-0.0775	-0.0884	-0.0769	-0.0858
	(0.00599)	(0.00692)	(0.00575)	(0.00670)
Ln mileage × Electric	-0.0228	-0.0126	-0.0375	-0.0336
	(0.0105)	(0.0135)	(0.00491)	(0.00620)
Only the vehicles that are 5 years or younger	Y	N	Y	N
Year × fuel fixed effects	Y	Y	Y	Y
Dealer fixed effects	Y	Y	Y	Y
Make fixed effects	N	N	Y	Y
Observations	378 357	452 743	378 357	452 743
R^2	0.856	0.864	0.875	0.882

Gasoline vehicles are the baseline.

Baseline is the vehicles from 2016-2021. Early refers to the vehicles from 2011-2015.

Dependent variable is ln of the secondhand price.

Standard errors clustered on make, in parentheses.

There are 61 clusters in (1) and (3) and 62 clusters in (2) and (4).

Year fixed effects are based on the year the vehicle is sold/advertised.

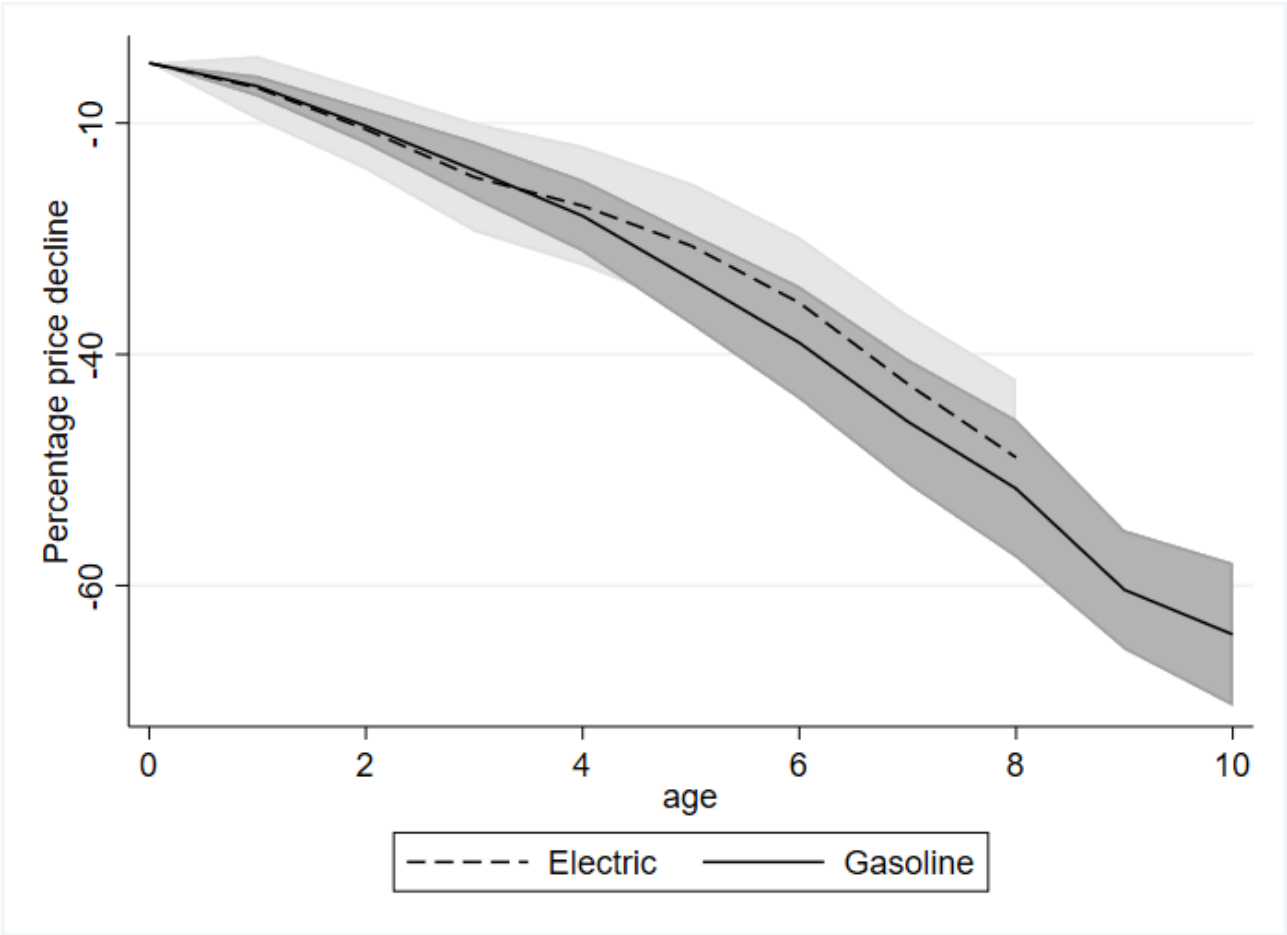
We use a dummy on those observations that have missing mileage
and those that have missing new car price.

Table A-14: Different price categories.

	(1) Over p75	(2) Over p50	(3) Below p50	(4) Below p25
Age	-0.105	-0.102	-0.111	-0.106
	(0.0117)	(0.00894)	(0.00489)	(0.00613)
Electric × Age	0.0424	0.0254	-0.0639	-0.0768
	(0.0131)	(0.0104)	(0.0185)	(0.0173)
Ln new price	0.991	0.951	1.120	1.195
	(0.0410)	(0.0400)	(0.0324)	(0.0499)
Ln mileage × Gasoline	-0.0862	-0.0698	-0.0789	-0.0900
	(0.0106)	(0.00899)	(0.00709)	(0.00461)
Ln mileage × Electric	-0.0634	-0.0434	-0.000746	-0.0162
	(0.00616)	(0.00991)	(0.0116)	(0.0129)
Year × fuel fixed effects	Y	Y	Y	Y
Dealer fixed effects	Y	Y	Y	Y
Observations	66 348	119 285	326 537	208 895
R^2	0.779	0.810	0.818	0.811

Dependent variable is ln of the secondhand price.
Standard errors clustered on make × fuel, in parentheses.
There are 39 clusters in (1), 54 clusters in (2), 50 clusters in (3) and 44 clusters in (4).
Gasoline vehicles are the baseline. Year times fuel fixed effects are based on the year the vehicle is sold/advertised.
p25, p50 and p75 refers to the statistics of the new vehicle price for the vehicles of all fuel types that are advertised on finn.no.
The 75th percentile is 461 275 NOK, the 50th percentile is 359 900 NOK and the 25th percentile is 275 600 NOK.
73% of the electric vehicles that are over the median is Tesla.
79% of the electric vehicles that are over the 75th percentile is Tesla.
Those that have missing new vehicle price is not part of this analysis (6921 observations).
We use a dummy on those observations that have missing mileage.

Figure A-3: The price path of electric vs gasoline vehicles, both with price of the new vehicle over the median.



The grey area is the 95% confidence interval. The standard errors are clustered on make × fuel.

Table A-15: The cars grouped into when they where new.

	(1) New in 2011-2013	(2) New in 2014-2016	(3) New in 2017-2021
Age	-0.129	-0.0850	-0.0553
	(0.00802)	(0.00881)	(0.00879)
Electric × Age	-0.215	-0.0336	-0.0377**
	(0.0776)	(0.0389)	(0.0164)
Ln new price	1.085	1.113	1.031
	(0.0382)	(0.0337)	(0.0276)
Ln mileage × Gasoline	-0.108	-0.0906	-0.0799
	(0.00587)	(0.00938)	(0.0100)
Ln mileage × Electric	-0.00184	-0.0213	-0.0386
	(0.0625)	(0.0182)	(0.00372)
Year× fuel fixed effects	Y	Y	Y
Dealer fixed effects	Y	Y	Y
Observations	155 498	177 699	119 546
R^2	0.844	0.841	0.859

Dependent variable is ln of the secondhand price.
Standard errors clustered on make, in parentheses.
There are 54 clusters in (1), 53 clusters in (2) and 50 clusters in (3).
Gasoline vehicles are the baseline.
Year fixed effects are based on the year the vehicle is sold/advertised.
We use a dummy on those observations that have missing mileage and those that have missing new car price.

Table A-16: Comparing 0-3-year-old used vehicles sold in different time periods.

	(1) Sold in 2011-2013	(2) Sold in 2014-2017	(3) Sold in 2018-2021
Age	-0.0863	-0.0789	-0.0667
	(0.00953)	(0.00624)	(0.00697)
Electric × Age	-0.101	-0.0721	-0.0295
	(0.0186)	(0.0256)	(0.0136)
Ln new price	0.982	1.068	1.031
	(0.0227)	(0.0331)	(0.0205)
Ln mileage × Gasoline	-0.0392	-0.0678	-0.0836
	(0.00360)	(0.00707)	(0.00930)
Ln mileage × Electric	-0.0162	0.00223	-0.0379
	(0.00943)	(0.0206)	(0.00553)
Year × fuel fixed effects	Y	Y	Y
Dealer fixed effects	Y	Y	Y
Observations	18 929	109 123	145 100
R^2	0.814	0.852	0.856

Dependent variable is ln of the secondhand price.
Standard errors clustered on make, in parentheses.
There are 45 clusters in (1), 54 clusters in (2) and 53 clusters in (3).
Gasoline vehicles are the baseline.
Year × fuel fixed effects are based on the year the vehicle is sold/advertised.
We use a dummy on those observations that have missing mileage
and those that have missing new car price.

Table A-17: Comparing different age groups.

	(1)	(2)	(3)
	Age 0-3	Age 4-6	Age 7-10
Age	-0.0760	-0.117	-0.146
	(0.00435)	(0.00618)	(0.00889)
Electric × Age	-0.0351	-0.0673	-0.204
	(0.0140)	(0.0266)	(0.0549)
Ln new price	1.044	1.126	1.188
	(0.0143)	(0.0420)	(0.0470)
Ln mileage × Gasoline	-0.0690	-0.155	-0.294
	(0.00596)	(0.0120)	(0.0169)
Ln mileage × Electric	-0.0253	-0.0164	-0.0865
	(0.00708)	(0.0472)	(0.0964)
Year × fuel fixed effects	Y	Y	Y
Dealer fixed effects	Y	Y	Y
Observations	273 152	136 323	432 68
R^2	0.855	0.814	0.808

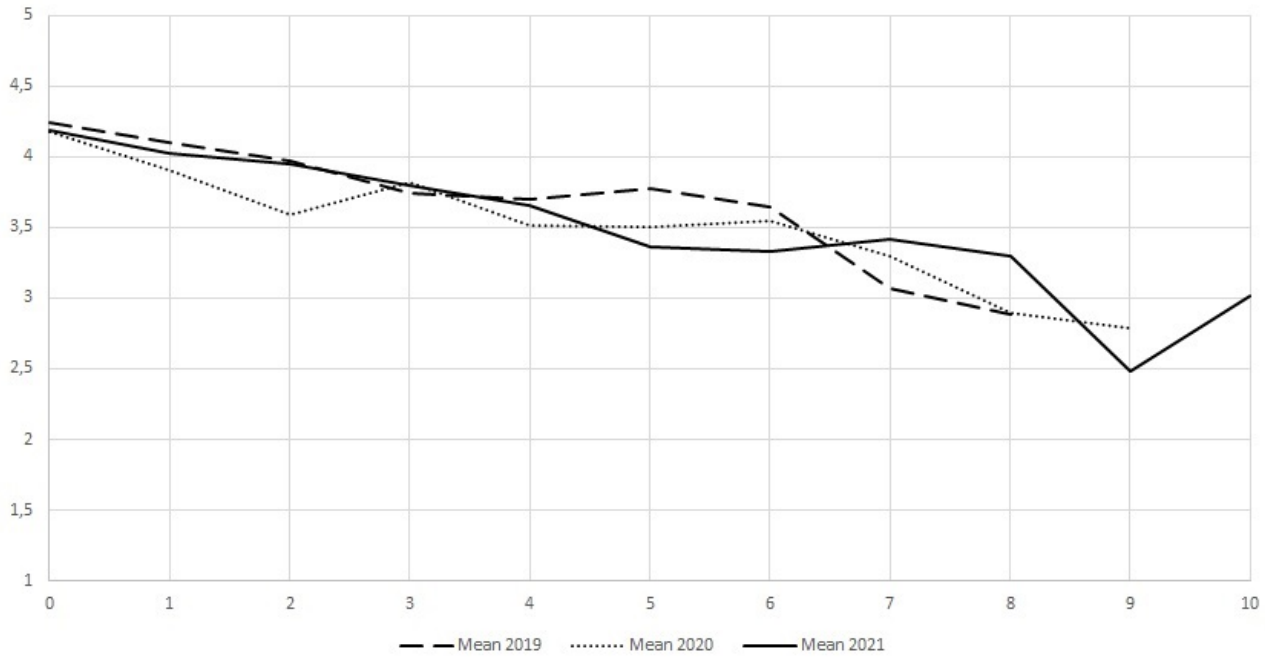
Dependent variable is ln of the secondhand price.
Standard errors clustered on make, in parentheses.
There are 61 clusters in (1), 54 clusters in (2) and 53 clusters in (3).
Gasoline vehicles are the baseline.
Year × fuel fixed effects are based on the year the vehicle is sold/advertised.
We use a dummy on those observations that have missing mileage
and those that have missing new car price.

Table A-18: Table 3 with all fuels and electric vehicles as the baseline.

	(1)	(2)	(3)	(4)	(5)
Age	-0.167	-0.166	-0.157	-0.171	-0.169
	(0.0193)	(0.0195)	(0.0203)	(0.0172)	(0.0200)
Gasoline × Age	0.0614	0.0615	0.0479	0.0571	0.0555
	(0.0194)	(0.0196)	(0.0201)	(0.0175)	(0.0200)
Hybrid × Age	0.0853	0.0872	0.0722	0.0889	0.0803
	(0.0200)	(0.0206)	(0.0212)	(0.0189)	(0.0204)
Diesel × Age	0.0303	0.0296	0.0210	0.0411	0.0274
	(0.0180)	(0.0183)	(0.0196)	(0.0151)	(0.0188)
Plug-in hybrid × Age	0.0772	0.0756	0.0590	0.0857	0.0720
	(0.0203)	(0.0187)	(0.0220)	(0.0168)	(0.0213)
Ln new price	1.092	1.058	1.027	1.094	1.083
	(0.0245)	(0.0271)	(0.0372)	(0.0319)	(0.0247)
Ln mileage × Electric	0.0148	0.0187	-0.00259	0.0131	0.00809
	(0.0121)	(0.0126)	(0.00933)	(0.0150)	(0.0121)
Ln mileage × Gasoline	-0.0777	-0.0767	-0.0778	-0.0613	-0.0786
	(0.00825)	(0.00741)	(0.00833)	(0.00587)	(0.00824)
Ln mileage × Hybrid	-0.116	-0.118	-0.113	-0.115	-0.118
	(0.0145)	(0.0142)	(0.0144)	(0.0155)	(0.0145)
Ln mileage × Diesel	-0.102	-0.0973	-0.104	-0.0763	-0.110
	(0.0133)	(0.0128)	(0.0138)	(0.00968)	(0.0135)
Ln mileage × Plug-in hybrid	-0.0605	-0.0590	-0.0521	-0.0619	-0.0626
	(0.0107)	(0.0122)	(0.00884)	(0.0115)	(0.0106)
Year × fuel fixed effects	Y	Y	Y	Y	Y
Dealer category fixed effects	Y	Y	Y	Y	N
Body style fixed effects	N	Y	N	N	N
Make fixed effects	N	N	Y	N	N
Taken out those with large variation in new vehicle price and those without new vehicle price	N	N	N	Y	N
Observations	1 167 132	1 167 132	1 167 132	633 630	1 167 132
R^2	0.844	0.847	0.856	0.891	0.840

Dependent variable is ln of the secondhand price.
Standard errors are clustered on make, in parentheses.
There are 66 clusters in all specifications except in (4) where there are 49 clusters.
Year fixed effects are based on the year the vehicle is sold/advertised.
Electric vehicles are the baseline.
We use a dummy on those observations that have missing mileage and those that have missing new car price.
Hydrogen and gas vehicles are not part of this as there are few observations.

Figure A-4: Mean of the answers to the question about whether the battery has degraded since the car was new.



Notes: The higher the better experience of the battery from 1-5.

D.1 Makes

There is a large difference in the average price fall between the different makes, which can be seen in Figure A-5. This can be due to different vintage or age of the cars, since electric Nissan entered the market in 2011, while electric Jaguar entered the market in 2018, but there can also be other reasons. There is a pattern where makes with large price fall have small cars with four seats (Smart, Fiat, Mitsubishi, Peugeot, Citroën).[22] Further, the majority of Ford's and Renault's models cannot fast charge, and the price fall of these cars is also above average of electric vehicles.[23]

The majority of the used cars sold from Tesla, Opel, Jaguar, Audi and Polestar have range above 400 km, and these makes have less than 10% price fall. Polestar has a price increase. Hyundai, which has a price fall in the same magnitude as Opel, has a model with range above 400 km (Hyundai Kona with range 449 km), but the sample also include Hyundai Ioniq which has 180 km[24]-311 km.

We also make this plot controlling for when the new vehicle price when the car was sold, instead of when the car was new, in Appendix Figure A-6. This changes the estimate for some of the makes, for instance Tesla.

We compare the price path of some specific models and makes. The most sold secondhand electric model, Nissan Leaf, compared to the most sold secondhand gasoline model, Volkswagen Golf, (see Table A-8) can be seen in Figure A-7.

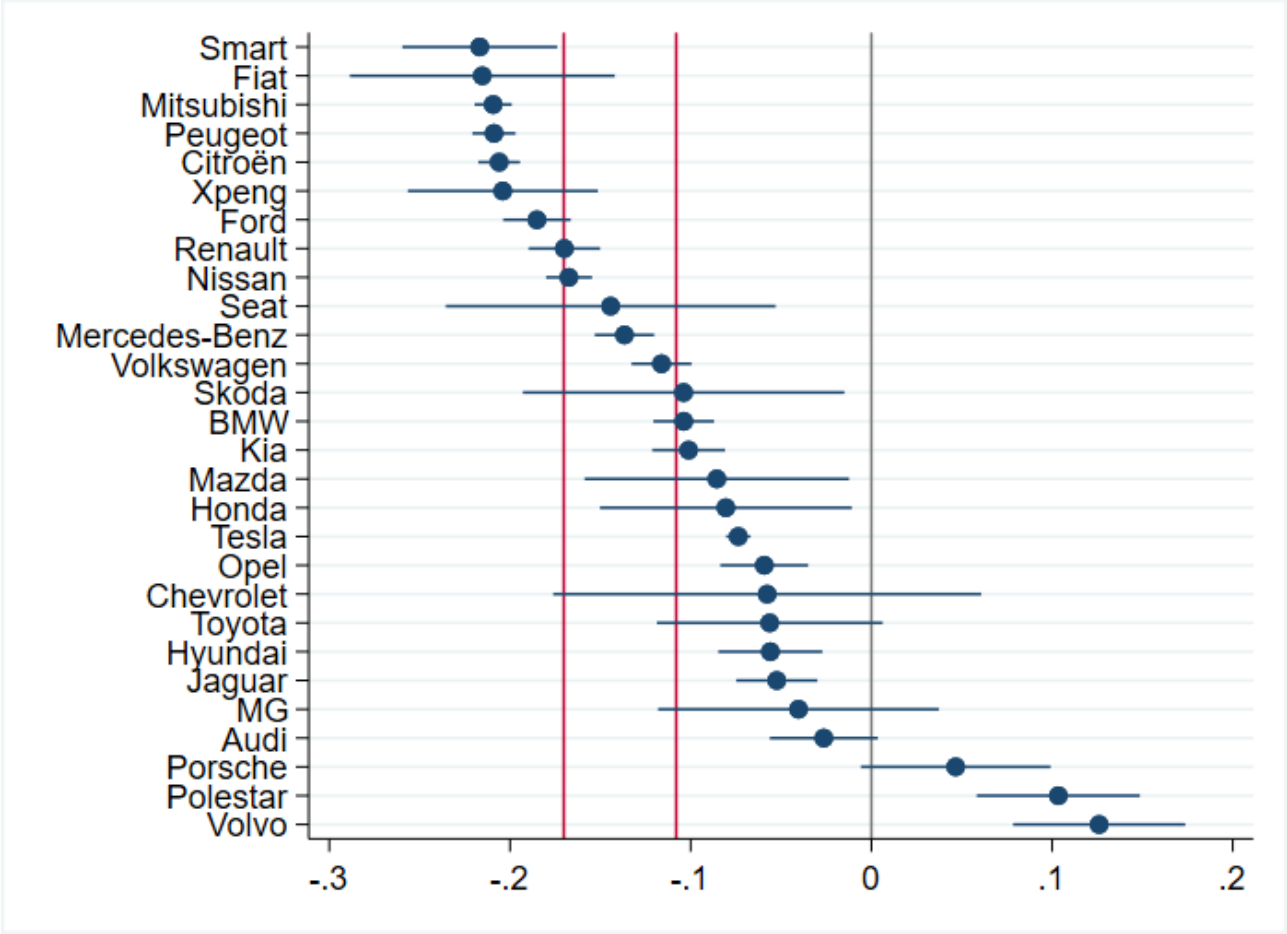
In Figure A-8 we compare gasoline vehicles where the new car price more than the median price of new vehicles with Tesla in the same price range. We see that Tesla fall less in price than gasoline vehicles.

[22]The exception is BMW which has a price fall close to the average for gasoline vehicles.

[23]Mercedes-Benz B-class can also not fast charge, but the price fall of this make is close to the average of electric vehicles. Toyota have not until recently supplied full electric vehicles and the Toyotas that is part of this sample is 147 RAV4 that was new during the years 2012-2015.

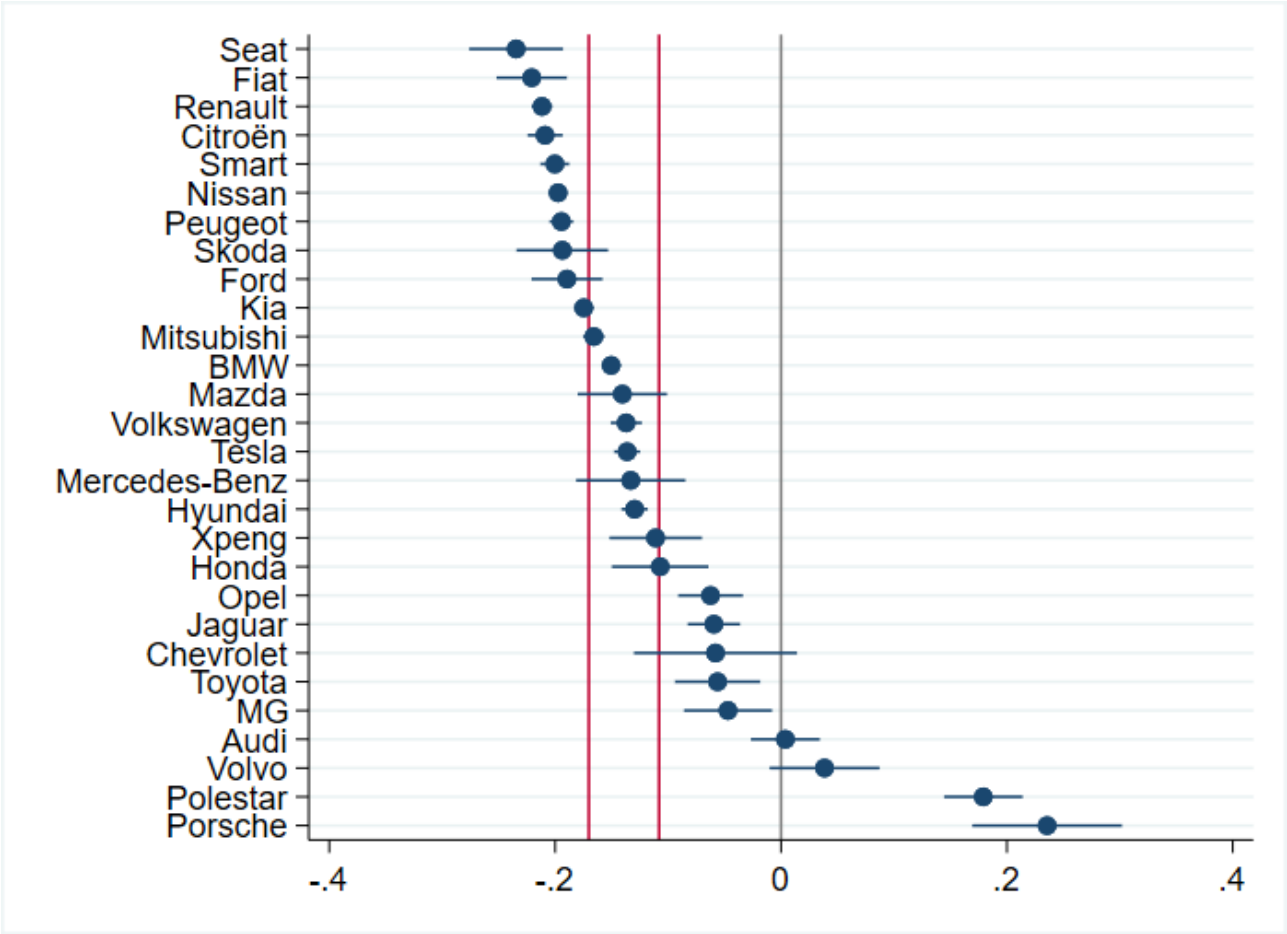
[24]The range is converted from NEDC range, see the Appendix B.3.1 for explanation.

Figure A-5: The average price fall for electric vehicles of different makes.



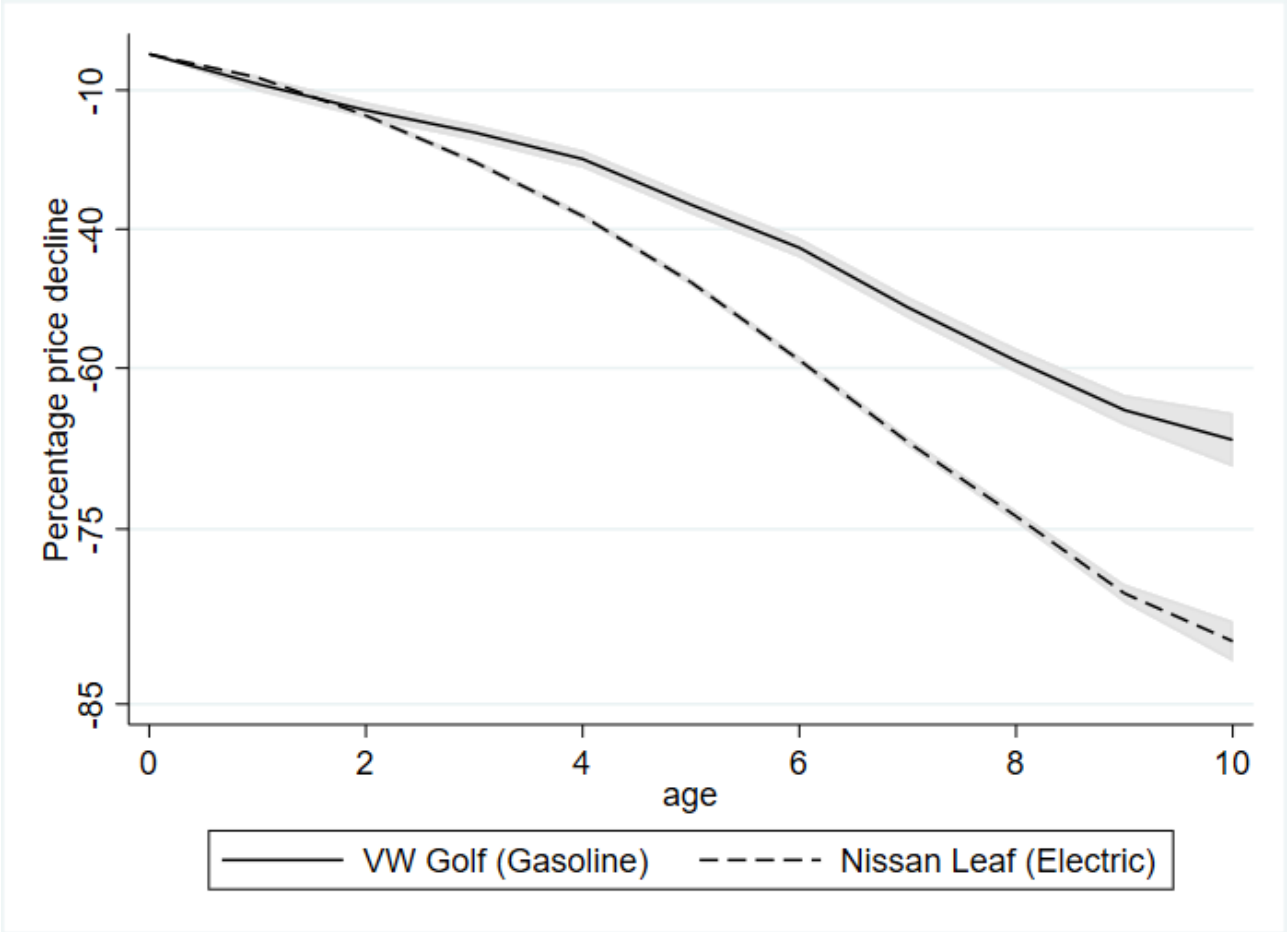
Notes: The red lines mark the average price fall for electric vehicles (-0.173) and the average price fall for gasoline vehicles (-0.106), based on the result in column 1 in Table 3. The grey line mark 0.

Figure A-6: Price fall for different makes controlling for the price of the new model when the car was sold, not when the car was new.



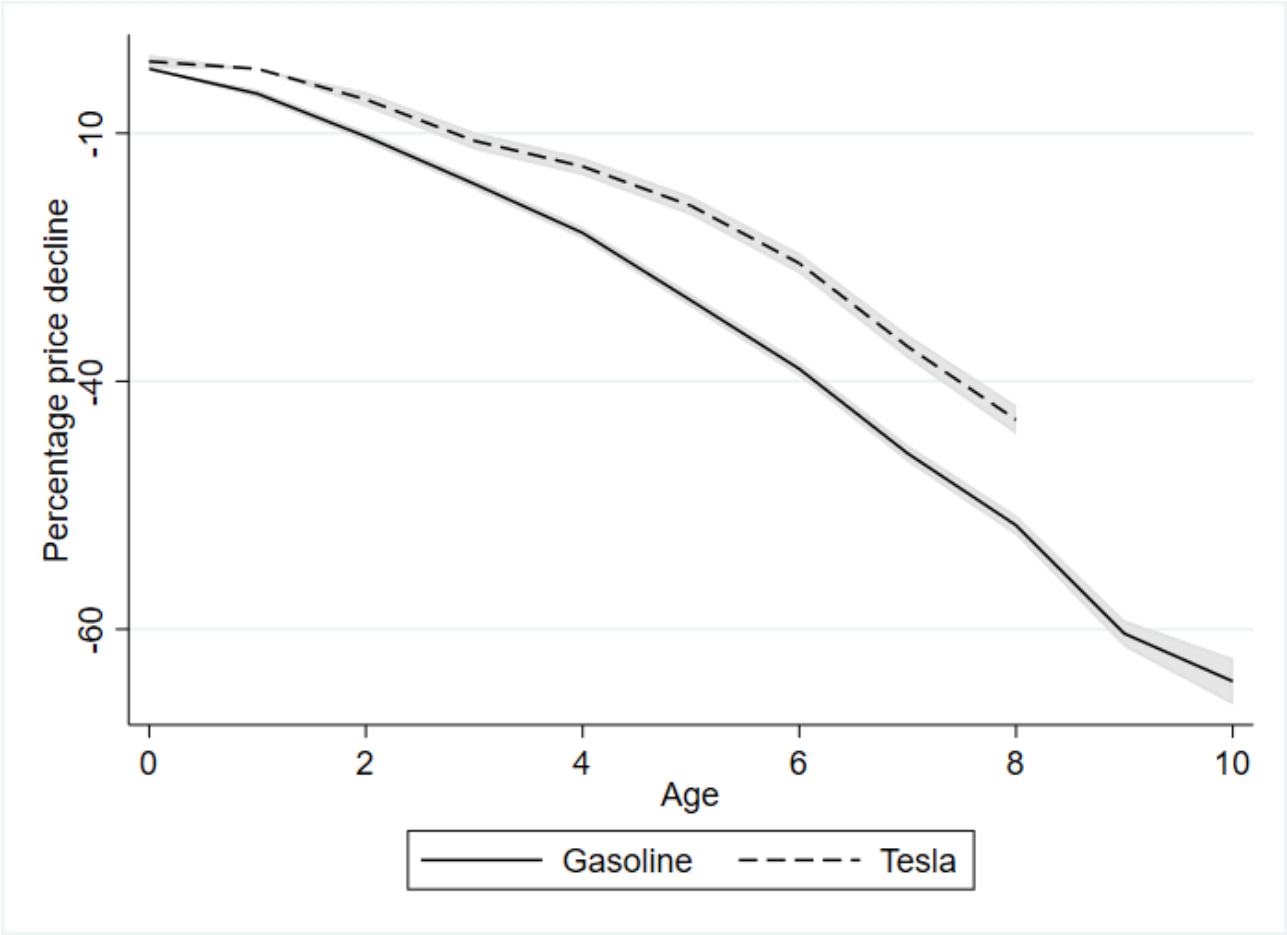
Notes: The red lines mark the average price fall for electric vehicles (-0.173) and the average price fall for gasoline vehicles (-0.106), based on the result in column 1 in Table 3. The grey line mark 0.

Figure A-7: Price path of the most sold used electric vehicle Nissan Leaf, compared to the most sold used gasoline vehicle, Volkswagen Golf.



The grey area is the 95% confidence interval. The standard errors are robust.

Figure A-8: The price path of Tesla vs gasoline vehicles.



Notes: The grey area is the 95% confidence interval. Here we compare the Teslas and gasoline vehicles that both have new vehicle price over the median. The standard errors are robust.

E Robustness

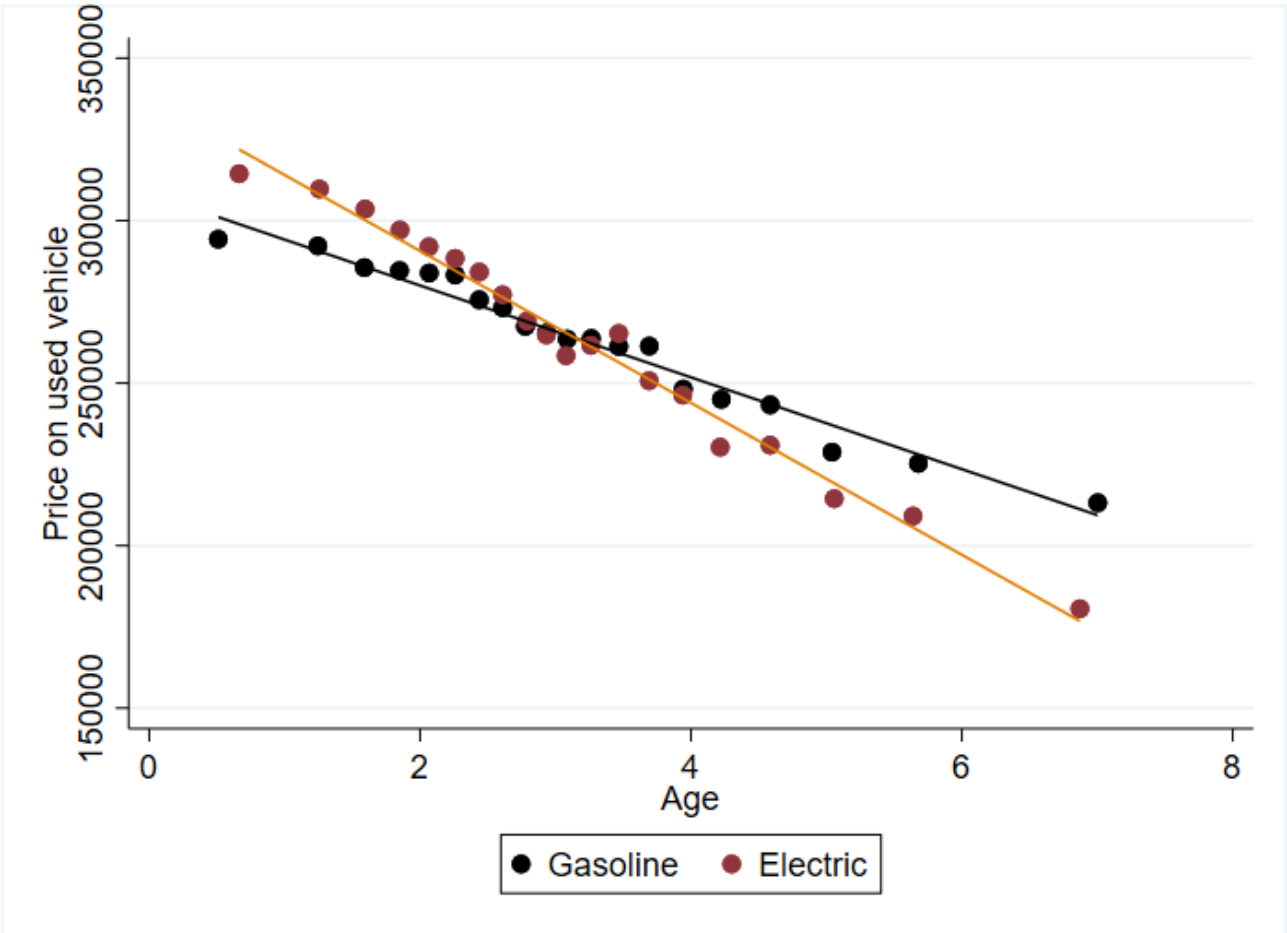


Figure A-9: Binned scatter plot of the data with prices in absolute values.

Table A-19: Controlling for many variables.

	(1)
Age	-0.112***
	(0.00237)
Electric × Age	-0.0430***
	(0.00679)
Ln new price	0.151
	(0.0398)
Ln mileage × Gasoline	-0.0745
	(0.00440)
Ln mileage × Electric	-0.0320
	(0.00498)
Dealer category: Private seller	-0.102
	(0.00786)
Dealer category: Professional car seller (not the make's own)	-0.0549
	(0.00928)
Engine effect	0.00000714
	(0.0000193)
Number of seats	0.000125
	(0.000591)
Year × fuel fixed effects	Y
Body style fixed effects	Y
Make fixed effects	Y
Model fixed effects	Y
Transmission fixed effects	Y
Wheel drive fixed effects	Y
Color fixed effects	Y
Observations	452 743
R^2	0.924

Dependent variable is ln of the secondhand price.
Gasoline vehicles are the baseline.
Among dealer categories are the make's professional car sellers baseline.
Year fixed effects are based on the year the vehicle is sold/advertised.
Standard errors clustered on make, in parentheses.
There are 62 clusters.
We use a dummy on those observations that have missing mileage
and those that have missing new car price.

Table A-20: Table 3 with new vehicle price the year the vehicle is sold, not the year the vehicle is new.

	(1)	(2)	(3)	(4)	(5)
Age	-0.137	-0.135	-0.141	-0.147	-0.162
	(0.00491)	(0.00460)	(0.00464)	(0.00627)	(0.00900)
Electric × Age	-0.0442	-0.0442	-0.0301	-0.0353	-0.134
	(0.0123)	(0.0128)	(0.0109)	(0.0126)	(0.0348)
Ln new price when sold	1.056	1.015	0.905	1.064	0.0208
	(0.0169)	(0.0224)	(0.0223)	(0.0178)	(0.00756)
Ln mileage × Gasoline	-0.0634	-0.0613	-0.0616	-0.0374	-0.00940
	(0.00795)	(0.00694)	(0.00819)	(0.00705)	(0.0162)
Ln mileage × Electric	-0.0327	-0.0255	-0.0351	-0.0305	0.160
	(0.00586)	(0.00611)	(0.00481)	(0.00606)	(0.108)
Year × fuel fixed effects	Y	Y	Y	Y	Y
Dealer fixed effects	Y	Y	Y	Y	N
Body style fixed effects	N	Y	N	N	N
Make fixed effects	N	N	Y	N	N
Taken out those with large variation in new vehicle price and those without new vehicle price	N	N	N	Y	N
Observations	452 743	452 743	452 743	283 785	452 743
R^2	0.794	0.796	0.825	0.821	0.384

Dependent variable is ln of the secondhand price.

Standard errors clustered on make, in parentheses. There are 62 clusters in all but in (4) where there are 44 clusters.

Gasoline vehicles are the baseline. Year fixed effects are based on the year the vehicle is sold/advertised.

We use a dummy on those observations that have missing mileage and those that have missing new car price.

Table A-21: Table 3 with new vehicle price and fuel interacted.

	(1)	(2)	(3)	(4)	(5)
Age	-0.108	-0.106	-0.111	-0.114	-0.113
	(0.00468)	(0.00440)	(0.00402)	(0.00565)	(0.00446)
Electric × Age	-0.0542	-0.0543	-0.0498	-0.0567	-0.0551
	(0.0214)	(0.0224)	(0.0204)	(0.0191)	(0.0174)
Ln new price × Gasoline	1.065	1.041	1.024	1.090	1.062
	(0.0256)	(0.0283)	(0.0307)	(0.0270)	(0.0265)
Ln new price × Electric	1.091	1.063	0.888	1.095	1.067
	(0.0332)	(0.0435)	(0.0487)	(0.0784)	(0.0328)
Ln mileage × Gasoline	-0.0741	-0.0748	-0.0744	-0.0612	-0.0768
	(0.00723)	(0.00607)	(0.00693)	(0.00573)	(0.00735)
Ln mileage × Electric	0.00874	0.0119	-0.00505	0.0137	0.00766
	(0.0108)	(0.0115)	(0.00842)	(0.0137)	(0.0106)
Year × fuel fixed effects	Y	Y	Y	Y	Y
Dealer fixed effects	Y	Y	Y	Y	N
Body style fixed effects	N	Y	N	N	N
Make fixed effects	N	N	Y	N	N
Taken out those with large variation in new vehicle price and those without new vehicle price	N	N	N	Y	N
Observations	452 743	452 743	452 743	283 785	452 743
R^2	0.867	0.868	0.882	0.899	0.862

Dependent variable is ln of the secondhand price.

Standard errors clustered on make, in parentheses. There are 62 clusters in all but specification (4), where there are 44 clusters.

Gasoline vehicles are the baseline. Year fixed effects are based on the year the vehicle is sold/advertised.

We use a dummy on those observations that have missing mileage and those that have missing new car price.

Table A-22: Table 3 without those with age=0.

	(1)	(2)	(3)	(4)	(5)
Age	-0.106	-0.105	-0.111	-0.113	-0.114
	(0.00473)	(0.00427)	(0.00413)	(0.00579)	(0.00459)
Electric X Age	-0.0676	-0.0675	-0.0485	-0.0623	-0.0617
	(0.0197)	(0.0203)	(0.0214)	(0.0174)	(0.0203)
Ln new price	1.081	1.060	1.006	1.107	1.074
	(0.0265)	(0.0323)	(0.0349)	(0.0337)	(0.0266)
Ln mileage X Gasoline	-0.102	-0.103	-0.0984	-0.0851	-0.102
	(0.00847)	(0.00708)	(0.00812)	(0.00589)	(0.00854)
Ln mileage X Electric	0.00716	0.00934	-0.0205	-0.00164	-0.00127
	(0.0148)	(0.0152)	(0.00862)	(0.0169)	(0.0149)
Year × fuel fixed effects	Y	Y	Y	Y	Y
Dealer fixed effects	Y	Y	Y	Y	N
Body style fixed effects	N	Y	N	N	N
Make fixed effects	N	N	Y	N	N
Taken out those with large variation in new vehicle price and those without new vehicle price	N	N	N	Y	N
Observations	407 236	407 236	407 236	251 266	407 236
R^2	0.852	0.854	0.873	0.894	0.849

Dependent variable is ln of the secondhand price.

Standard errors clustered on make, in parentheses. There are 62 clusters in all but in (4) where there are 44 clusters.

Gasoline vehicles are the baseline. Year fixed effects are based on the year the vehicle is sold/advertised.

We use a dummy on those observations that have missing mileage and those that have missing new car price.

Table A-23: Table 3 without dummy on those that have missing new vehicle price and mileage, meaning that the sample is smaller.

	(1)	(2)	(3)	(4)	(5)
Age	-0.111	-0.110	-0.114	-0.114	-0.119
	(0.00458)	(0.00417)	(0.00399)	(0.00572)	(0.00440)
Electric × Age	-0.0539	-0.0536	-0.0406	-0.0581	-0.0480
	(0.0202)	(0.0208)	(0.0209)	(0.0177)	(0.0207)
Ln new price	1.073	1.048	1.015	1.093	1.065
	(0.0242)	(0.0304)	(0.0293)	(0.0315)	(0.0241)
Ln mileage × Gasoline -0.0709	-0.0716	-0.0715	-0.0621	-0.0716	
	(0.00713)	(0.00573)	(0.00711)	(0.00584)	(0.00709)
Ln mileage × Electric	0.0119	0.0145	-0.00429	0.0145	0.00468
	(0.0117)	(0.0121)	(0.00931)	(0.0149)	(0.0117)
Year × fuel fixed effects	Y	Y	Y	Y	Y
Dealer fixed effects	Y	Y	Y	Y	N
Body style fixed effects	N	Y	N	N	N
Make fixed effects	N	N	Y	N	N
Taken out those with large variation in new vehicle price and those without new vehicle price	N	N	N	Y	N
Observations	428 882	428 882	428 882	269 489	428 882
R^2	0.880	0.882	0.889	0.897	0.877

Dependent variable is log of the secondhand price.

Standard errors clustered on make, in parentheses. There are 44 clusters in all but column 4, where there are 43 clusters.

The sample is smaller by 23 861 observations.

Gasoline vehicles are the baseline. Year fixed effects are based on the year the vehicle is sold/advertised.

Table A-24: Table 3 with absolute values instead of ln values.

	(1)	(2)	(3)	(4)	(5)
Age	-23166.3	-21761.1	-25252.5	-22374.3	-23315.9
	(3738.7)	(3452.5)	(3331.9)	(3299.2)	(3615.2)
Electric × Age	-11108.9	-11053.5	-1970.8	-8113.7	-10983.0
	(4306.4)	(3801.1)	(4228.8)	(3958.5)	(4274.4)
New car price 0.720	0.697	0.610	0.709	0.721	
	(0.0406)	(0.0404)	(0.0239)	(0.0444)	(0.0403)
Mileage × Gasoline	-0.695	-0.733	-0.618	-0.618	-0.694
	(0.126)	(0.107)	(0.104)	(0.0876)	(0.128)
Mileage × Electric	-0.0889	-0.0525	-0.585	-0.185	-0.100
	(0.122)	(0.119)	(0.173)	(0.149)	(0.123)
Year × fuel fixed effects	Y	Y	Y	Y	Y
Dealer fixed effects	Y	Y	Y	Y	N
Body style fixed effects	N	Y	N	N	N
Make fixed effects	N	N	Y	N	N
Taken out those with large variation in new vehicle price and those without new vehicle price	N	N	N	Y	N
Observations	452 743	452 743	452 743	283 785	452 743
R^2	0.789	0.793	0.835	0.868	0.789

Dependent variable is log of the secondhand price.

Standard errors clustered on make, in parentheses. There are 62 clusters in all but in (4) where there are 44 clusters.

Gasoline vehicles are the baseline. Year fixed effects are based on the year the vehicle is sold/advertised.

We use a dummy on those observations that have missing mileage and those that have missing new car price.

Table A-25: Table 3 with clusters based on make × fuel.

	(1)	(2)	(3)	(4)	(5)
Age	-0.108	-0.106	-0.112	-0.114	-0.115
	(0.00452)	(0.00417)	(0.00369)	(0.00562)	(0.00441)
Electric × Age	-0.0622	-0.0618	-0.0446	-0.0571	-0.0567
	(0.0199)	(0.0203)	(0.0199)	(0.0184)	(0.0205)
Ln new price	1.070	1.050	0.999	1.091	1.063
	(0.0240)	(0.0297)	(0.0281)	(0.0282)	(0.0238)
Ln mileage × Gasoline	-0.0767	-0.0772	-0.0750	-0.0613	-0.0773
	(0.00769)	(0.00659)	(0.00710)	(0.00581)	(0.00768)
Ln mileage × Electric	0.0179	0.0199	-0.00372	0.0138	0.0109
	(0.0128)	(0.0130)	(0.00801)	(0.0149)	(0.0130)
Year × fuel fixed effects	Y	Y	Y	Y	Y
Dealer fixed effects	Y	Y	Y	Y	N
Body style fixed effects	N	Y	N	N	N
Make fixed effects	N	N	Y	N	N
Taken out those with large variation in new vehicle price and those without new vehicle price	N	N	N	Y	N
Observations	452 743	452 743	452 743	283 785	452 743
R^2	0.859	0.861	0.878	0.899	0.857

Dependent variable is ln of the secondhand price.

Standard errors clustered on make, in parentheses.

There are 90 clusters in all but specification (4), where there are 68 clusters.

Gasoline vehicles are the baseline. Year fixed effects are based on the year the vehicle is sold/advertised.

We use a dummy on those observations that have missing mileage and those that have missing new car price.

Table A-26: Table 3 with clusters based on make × year the vehicle is new.

	(1)	(2)	(3)	(4)	(5)
Age	-0.108	-0.106	-0.112	-0.114	-0.115
	(0.00338)	(0.00326)	(0.00296)	(0.00416)	(0.00339)
Electric × Age	-0.0622	-0.0618	-0.0446	-0.0571	-0.0567
	(0.0123)	(0.0125)	(0.0113)	(0.0123)	(0.0124)
Ln new price	1.070	1.050	0.999	1.091	1.063
	(0.0178)	(0.0250)	(0.0173)	(0.0243)	(0.0179)
Ln mileage × Gasoline	-0.0767	-0.0772	-0.0750	-0.0613	-0.0773
	(0.00392)	(0.00360)	(0.00357)	(0.00394)	(0.00395)
Ln mileage × Electric	0.0179	0.0199	-0.00372	0.0138	0.0109
	(0.0117)	(0.0116)	(0.00710)	(0.0121)	(0.0117)
Year × fuel fixed effects	Y	Y	Y	Y	Y
Dealer fixed effects	Y	Y	Y	Y	N
Body style fixed effects	N	Y	N	N	N
Make fixed effects	N	N	Y	N	N
Taken out those with large variation in new vehicle price and those without new vehicle price	N	N	N	Y	N
Observations	452 743	452 743	452 743	283 785	452 743
R^2	0.859	0.861	0.878	0.899	0.857

Dependent variable is ln of the secondhand price.

Standard errors clustered on make × the year the vehicle is new, in parentheses.

There are 482 clusters in all but specification (4), where there are 332 clusters.

Gasoline vehicles are the baseline. Year fixed effects are based on the year the vehicle is sold/advertised.

We use a dummy on those observations that have missing mileage and those that have missing new car price.