Master's thesis

NTNU
Norwegian University of Science and Technology

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A Hedonic Pricing Model for Second-Hand Cars in Norway Testing Prospect Theory Assertions

Master's thesis in Economics and Business Administration
Supervisor: Denis M. Becker
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Kunnskap for en bedre verden

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Foreword

This master’s thesis is written as a conclusion to a two-year study in “economics and business administration” at NTNU Business school in the period 2020-2022. It has been written by two students with different profiles, whereas Saif Al-Yassin studies finance and Håvard Brekke studies Business Analytics. The writing of the thesis has been a valuable and challenging process, not least a process that has been very educational. In testing prospect theoretical behavior and creating a hedonic pricing model for the second-hand car market, we hope and believe the thesis could be beneficial and educational for future readers. We would like to thank Peter Wakker, an expert in the area of prospect theory, who pointed us in the right direction with regards to literature. Also, we wish to thank OFV (Opplysningsrådet for veitrafikk) for providing data and insight. Finally, we would like to thank our supervisor during the period, Denis M. Becker. He has been an important supporter and resource for us and has given us good constructive feedback on the assignment the whole period. The contents of this thesis and the opinions expressed therein are the authors sole responsibility and do not reflect opinions and beliefs of NTNU.

Trondheim, May 2022

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Abstract

This paper investigates prospect theoretic implications in the price formation of used cars using a hedonic model. We attempt to replicate the findings of Prieto et al (2014), which found indications of asymmetric and nonlinear effects of annual mileage on price using the method proposed by Betts & Taran (2007). We find some indications of similar pricing curvature but end up concluding that the approach used by Prieto et al. (2014) seems unable to assert that individuals employ prospect theoretic behavior when buying used cars. Mainly because buying a car is a complex purchasing decision, with more factors at play than in classical laboratory prospect theoretic articles. It follows from this that using market level data instead of individual level choice data hinders establishing a causal connection between the observed pricing patterns and individual choice characteristics. With respect to the general hedonic model and other pricing irregularities, we find evidence for people not pricing age in a higher fidelity than years. Also, we do not find evidence for a marked price drop when cars have crossed 100.000 kilometers, that Kooreman & Han (2006) found in the Netherlands.

Sammendrag

Denne artikkelen undersøker prospektteoretiske implikasjoner i prisdannelsen på bruktbiler ved bruk av en hedonisk modell. Vi forsøker å replikere funnene til Prieto et al. (2014), som fant indikasjoner på asymmetriske og ikke-lineære effekter av årlig kjørelengde på prisen ved å bruke metoden foreslått av Betts & Taran (2007). Vi finner noen indikasjoner på lignende priskurvatur, men ender opp med å konkludere med at tilnærmingen brukt av Prieto et al. (2014) synes å være ute av stand til å hevde at individer bruker prospektteoretisk atferd når de kjøper bruktbiler. Hovedsakelig fordi å kjøpe en bil er en kompleks kjøpsbeslutning, med mange flere faktorer som spiller inn enn i klassiske prospektteoretiske artikler med eksperimenter utført i kontrollerte laboratorie-settinger. Det følger av dette at bruk av data på markedsnivå i stedet for valgdata på individnivå vanskelig-gjører det å etablere en årsakssammenheng mellom de observerte prismønstrene og individuelle valgkarakteristikker. Med hensyn til den generelle hedoniske modellen og andre prisuregelmessigheter, finner vi bevis for at folk ikke priser alder på biler med en høyere oppløsning enn år. Vi finner heller ikke bevis for et markant prisfall når biler har krysset 100.000 kilometer, som Kooreman & Han (2006) fant i Nederland.

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1 Introduction

This thesis is motivated by previous research by Prieto et al. (2014) who found signs of prospect theory in the French used car market. The purpose of this paper is to test whether prospect theory also can be confirmed on data from the Norwegian car market. We build a hedonic pricing model that enable us to quantify what characteristics influences car prices. This helps us investigate whether prospect theory is able to predict pricing irregularities with respect to mileage and model year. These factors are indicators of quality that influence the expected future mileage left. Following the method of Betts & Taran (2006, 2007) and Prieto et al. (2014) we consider car reliability using the annual mileage as a proxy for how the market assesses the potential for future usage. We focus on deviations from observed annual mileage to various plausible reference annual mileages. Deviations from the reference annual mileage allow us to test for prospect theory (PT) (Kahneman & Tversky, 1979) and its implications in the formation of used car prices.

Prospect theory posits that when individuals make decisions under uncertainty, a loss or gain frame is applied, reliant on some reference point taken in the decision phase. It further states that the utility function is curved differently for losses and gain states (convex for losses and concave for gains). Therefore, we expect to find pricing curvatures in concordance with these predictions. An obvious question to ask is what the reference point is likely to be in a complex decision such as a car purchase. Previous papers including Betts & Taran (2007) and Prieto et al. (2014) propose average yearly miles driven as a possible reference point. In this paper, we try to replicate the findings of Prieto et al. (2014), a paper which concluded that it found evidence for prospect theoretic curvature in pricing relating to yearly mileage. More specifically it found different pricing curvature below and above their reference point annual mileage, which suggests that consumers buying cars apply a framing procedure in accordance with PT. We argue in the discussion section with a suspicion that this is a misapplication of PT, and that the findings of Prieto et al. (2014) may be due to other factors than PT framing effects.

The hedonic framework we use to price cars suggest that the value and price of a good is best thought of as the sum of the value of its characteristics. In this thesis the framework will be used in the second-hand car market, where it looks at internal characteristics in a vehicle such as; transmission, mileage, seats etc. and external factors like the car's location, first time registration etc. This will help to determine characteristics consumers value when buying a used car. The pricing of characteristics from the hedonic model is what ultimately enables us to capture the pricing curvature from PT.

2 Theory

2.1 Prospect theory

The neoclassical theory of utility is one of the cornerstones of modern economic theory, and therefore widely understood and discussed in the economic and financial field. The same cannot be said for prospect theory, and it can therefore be difficult for some to see the main differences between prospect theory and expected utility theory. Both theories are based on choices under uncertainty and to some degree uses utility as a basis for choices. The simpler explanation to the main differences is that in the perspective of the expected utility theory, an individual's choice is based on the outcome with the highest utility given the presented objective probabilities of the choice. Prospect theory does not consider expected utility as the only criteria for choices. Therefore, an individual in the eyes of the prospect theory might end up making a choice that doesn't reward the highest utility, because the theory presents other reflections besides utility. One of the essential reflections within prospect theory that differs from expected utility theory, is that the prospect theoretical framework states that an individual's behavior differs depending on whether the choice is presented in a winning or a losing frame. i.e., one would react differently to the possibility of [gaining 100 with probability of 80% / sure gain of 75] and [losing 100 with probability of 80% / sure loss of 75]. The choices in these scenarios differ because prospect theory makes different assumptions then expected utility theory.

Looking at it with a more technical perspective, prospect theory differs from the expected utility theory in the sense of revising the three main elements in the theories of choice under uncertainty; 1) The object of choice, 2) a valuation rule, 3) characteristics of the functions. In expected utility theory these are; 1) probability distributions over wealth, 2) expected utility, and 3) concave function of wealth (Kahneman & Tversky, 1992). Traditionally, "the expected utility theory assumes that the expected utility of any bundle of uncertain prizes is equal to the utility of each prize weighted simply by the probability of that prize" (Harrison & Hey, 1994 p.47). Kahneman & Tversky (1992) proposed a revision of the three previously mentioned elements, where prospects are framed in terms of gains and losses; a two-part cumulative function as the valuation rule; and lastly an S-shaped function for value and an inverse S-shape function for probability weighting.

2.1.1 The probability weighting function

The probability weighting function is central to explaining phenomena such as lotteries and insurance. The basic idea is that in prospect theory, actors do not weigh probabilities by their objective percentages, but rather use a weighting transformation with the objective probability as an argument in its function. This weighting function over-values low probabilities and undervalues high probabilities, as per the pattern in figure 1. The dotted line represents the objective probabilities, while the solid line represents the weighted probabilities. When choosing between a 1% chance of winning 1000 dollars and a 100% chance of getting 10 dollars, the 1% is overweighted such that a lottery ticket purchasing decision can be explained within PT. The overweighting of small probabilities can also explain insurance decisions: The small but probable likelihood of an insurance triggering accident becomes overweighted and thus seems more valuable than the expected loss a rational agent would consider an insurance deal to be.

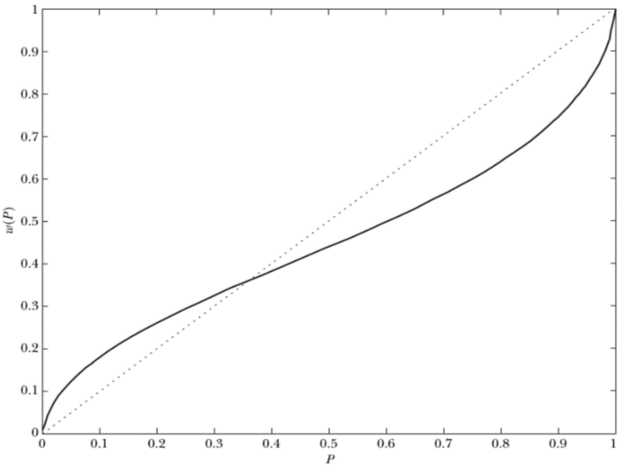


Figure 1: The probability weighting function from Barberis (2013), original version from Kahneman & Tversky (1992).

In cumulative prospect theory, the weighting function is applied on cumulative probabilities. For example to the probability of winning at least 1000 dollars, or opposite, the probability of one's car malfunctioning and thus incurring a loss of 2000 dollars or more in repair costs. The main takeaway is that the probability weighting function of a PT actor has more meaningful effects on the tail of the probability distribution. Thus, extreme events with small probabilities are likely to be given more attention and should be expected to influence more than what standard utility theory predicts.

2.1.2 Value function

As seen in the figure below, there is a difference in the steepness of the S-shaped value function for losses and gain frames where the curve is steeper for losses, argued with the effect of loss aversion. This is an effect where an individual much prefers the avoidance of losing, rather than gaining an equivalent amount. Furthermore, the concave and convex curvature shows that people tend to be risk averse over gains (concave), and risk seeking over losses (convex). To explain this, Kahneman & Tversky (1979) presented several problems showing the differences between positive and negative prospects. For example, what preferences subjects had between the chance of winning 4 000 at a probability of 80% or a sure gain of 3 000. This showed that 80% of the respondents preferred the sure gain of 3 000. On the losing side however, the subjects were given an 80% chance of losing 4 000, or a sure loss of 3 000. In this scenario, 92% of the respondents preferred an 80% chance of losing 4 000. Another important factor in the value function is the reference point. Kahneman & Tversky (1979) mention that the reference point usually corresponds to the current asset position in which case gains and losses coincide with the actual amount paid and or received. However, they mention that the location of the reference point and the perspective of gains and losses, can be affected by the formulation of the specific prospect and the decision maker´s expectations. This indicates that variability in reference points occur, which makes it a more complicated factor.

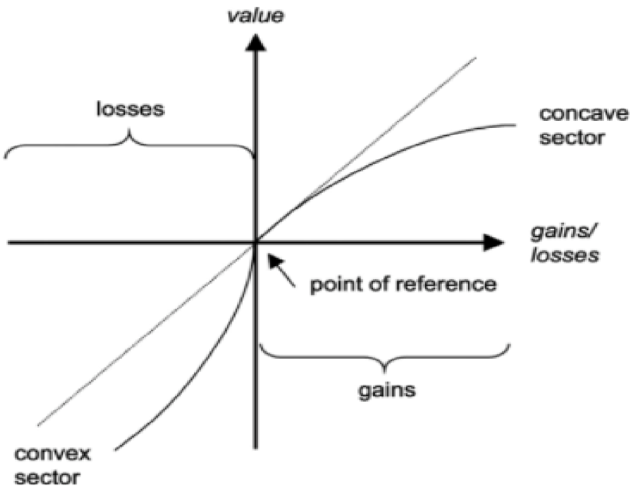


Figure 2: PT Value function from Prieto et al. (2014), originally from Kahneman & Tversky (1979)

Baillon et al. (2020) addresses the challenges in forming a reference point, and that interpreting evidence can be unclear due to data being consistent with several reference points at the same time. In other words, using PT in its simplest form with weighted probabilities and explicit payoffs makes the theory better testable. Once scenarios become more complex, like in purchasing a car, the theory becomes more challenging to assert.

2.1.3 More about the reference point

More than 40 years after its publication, PT is still widely recognized as the best available description of how individuals evaluate risk and uncertainty. It seems curious then, that there are relatively few well known and broadly accepted applications of PT in economics. Barberis has written an excellent article called Thirty Years of Prospect Theory in Economics: A Review and Assessment (2013), highlighting reasons why there have been lackluster empirical use of prospect theory outside narrow applications.

"*One might be tempted to conclude that, even if prospect theory is an excellent description of behavior in experimental settings, it is less relevant outside the laboratory. In my view, this lesson would be incorrect. Rather, the main reason that it has taken so long to apply prospect theory in economics is that [...] it is hard to know exactly how to apply it.*" (Barberis, 2013 p.1-2)

Barberis (2013) then goes on to talk about how the challenge of finding a reference point is one of the main issues in applying prospect theory. Kahneman & Tversky (1989) themselves acknowledge this weakness with the theory:

"*The introduction of psychological considerations (e.g framing) both enriches and complicates the analysis. Because the framing of decisions depends on the language of presentation, on the context of choice, and on the nature of display, our treatment of the process is necessarily informal and incomplete. We have identified several common rules for framing and have demonstrated their effects on choice, but have not provided a formal theory of framing*" (Kahneman & Tversky, 1989 p. 33).

This lack of a formal theory of framing (which entails picking a reference point) have led to a large variety in how to settle on reference points. One meaningful attempt to operationalize how people think about gains and losses comes from Koszegi & Rabin (2006). The authors propose a framework for prospect theory where the key idea is that the reference point people use to compute gains and losses, is their expectations or beliefs about outcomes held in the recent past. In particular they propose that people derive utility from the difference between consumption and expected consumption, where the utility function exhibits loss aversion and diminishing sensitivity. While this is an interesting attempt to formalize reference framing, in practice there still exists a large variety between practitioners in setting reference points.

Furthermore, in complex decisions such as a car purchase, utility and uncertainty stems from a lot of sources. Most PT literature have only done tests in a unidimensional setting. That is, the choice only derives utility from one factor, such as money or life years. Articles such as Kemel & Paraschiv (2013) have tested PT in two-dimensional decisions. But these articles still have transparent risks associated with them, instead of ambiguity which best describes the uncertainty in a car purchase. (Risk has stated probabilities of outcomes, in ambiguity the distribution of probabilities is unknown). Therefore, our paper is one of the first to test PT in what we call a complex decision (Except from Prieto et al. (2014) and Betts & Taran (2006), but these articles do not discuss the multitude of problems associated with this endeavor). The complexity, to sum up, stems from four factors: Multiple dimensions of choice and uncertainty, unclear what reference point variable to choose, market level data instead of individual level, and dealing with ambiguity instead of risk. Aforementioned papers have been written focusing on one of these aspects, but none have attempted with all four included – as we will discuss later, probably with good reason.

Taking all these challenges into consideration, our focus will be to see if we can find empirical evidence for PT predictions by replicating the method of Prieto et al. (2014) and Betts & Taran (2006, 2007). We will furthermore discuss the viability and validity of their suggested method focusing on the factors mentioned above.

2.2 Theoretical foundations of hedonic pricing models

The first article to introduce the hedonic pricing method was published by Andrew T. Court in 1939: "*Hedonic price indexes with automotive examples*". This contribution looked at the idea of pricing a commodity by the sum of its embodied characteristics, using time series data. A more rigorous theoretical utility foundation for heterogeneous goods was given by Lancaster (1966). Rosen (1974) incorporated Lancaster's utility foundation to create a theory of hedonic pricing functions. This has become a workhorse for valuing the characteristics of heterogeneous goods, and it is the ideas from his seminal paper we are going to use to price cars and their characteristics in this article.

There are two main reasons for applying hedonic models. The first one is to create pricing indices which examine prices and quality changes over time in heterogeneous markets. This approach is widespread in both housing and automobile literature, where Ohta & Griliches (1976) was one of the first attempts at applying Rosen's theory of hedonic pricing to create pricing indices in the used car market. The other main reason, which is why we apply the hedonic method, is in examining and understanding consumer demand for heterogeneous goods and its characteristics. In this spirit, articles such as Calmasur (2016) & Prieto et al. (2014) are examples.

In hedonic pricing, understanding the concept of implicit markets is important. Implicit markets denote the transaction of goods which are primarily or even exclusively traded in bundles. The explicit market with observable prices is for the bundles (e.g., car) as a whole. But the underlying assumption as to what creates these prices are the constitutive elements of the bundle. So, the consumer does not value a good as a whole, but rather considers the value of each attribute of the good and calculates what the total value of the bundle is for them. Besides implicit markets, it is also important to understand hedonic price functions. To understand what constitutes appropriate estimation techniques and how to interpret results, we need to start with knowing how heterogeneous hedonic markets can be expected to function.

We begin with a basic introduction to hedonic pricing as first discussed in Rosen's seminal paper from 1974. Consumers are considered to attain utility from consumption of a good which embodies a vector Z of J characteristics, plus consumption of the composite good I. They have a price function P(Z) which gives the price of the heterogeneous commodity, in this case a car, as a function of the characteristics in Z. The preferences of the consumer are represented by the utility function

$$\boldsymbol{U}(\boldsymbol{Z},\boldsymbol{I},\boldsymbol{a}) \qquad \textbf{(1)}$$

where a is a vector of both observed and unobserved parameters which characterize the preferences of the consumer.

From the utility function **(1)** we can find out the amount the consumer is willing to pay for a car as a function of its characteristics.

It is worth noting that the hedonic method operates within the revealed preferences paradigm. Assuming the choices consumers make reveals their inherent preferences makes willingness-to-pay the key method of discovering what these preferences are. An observant reader will notice that we do not have access to actual choice data, since the prices given on Finn.no are ask prices and not transaction prices. A discussion of this methodological issue is given more attention later in the text.

3 Data

The cross-sectional data we use have been collected from the website Finn.no using web-scraping in Python with the Requests and BeautifulSoup packages. Finn is a Norwegian online marketplace which facilitates consumer-to-consumer and business-to-consumer sales through its website, akin to eBay and Amazon. Thus, we have cars posted from both private persons and from professional retailers. The site contained about 60.000 car ads when the website was scraped on February 15th, 2022.

3.1 Website structure, data scraping and cleaning

Car ads on Finn are organized within four main data categories. Three of these include obligatory information which the seller must include, and which is done in an automatic way via inputting the register number of the vehicle. This means that we obtained complete data within these categories. The first one of the obligatory categories is the “name” category, which describes the car model. The second are its “main feature” category, which includes odometer value, fuel type, engine type and transmission. The third is the specifications category which include variables such as wheelbase, cylinder volume, co2-emissions and much more. The final category, which is not obligatory to fill in data on, is the “equipment list”. Here one can fill in about 70 different add-ons, such as A/C, seat warmer, parking camera, sport seats, cruise control and so forth. But using these data points in a statistical analysis is problematic since it is optional to inform about these items. With response rates ranging from 70% to 2%, it is hard to know if the lack of an item is due to the seller not bothering to answer or if it stems from an actual lack of the item in his vehicle. Thus, we cannot be sure what we are measuring with respect to the equipment list, and refrain from using it. In addition, consumers on FINN have available pictures of the vehicle and text often describing the condition of the vehicle in detail. These data points are also lacking in our analysis because of the challenge to meaningfully categorize and interpret such data.

Some data-cleaning was necessary in preparation to apply the dataset in statistical analysis. Firstly, ads from 2022 and before 2011 were removed. We removed ads from before 2011 because the variability was assumed to be too large in old models to be valuable in analysis - for example the likelihood of repairs and aspects not captured in the data points we have acquired was deemed too high. Furthermore, we removed all leasing cars because they are listed with monthly rent prices and not sales prices. We only kept the three most popular body types; SUV, 5-door hatchback, and station wagon. We also removed all-electric vehicles because they have different lifetime depreciation characteristics than fossil fueled cars. In the end, we removed all observations with missing values. This final action got us from about 28000 to 20651 observations, which is our final data set.

3.2 Descriptive statistics - introduction to dataset

Under is an overview and explanations of the variables included in our models. The gap line separates native variables available on Finn.no from transformed/constructed variables.

Table 1: Description variables

Variable	Description
lnprice	Natural logarithm of asking price in NOK
price	Asking price of the vehicle ad in NOK
kilometer	The vehicles driven mileage in kilometers
transmission	Dummy whether the vehicle has automatic or manual transmission, where manual = 0
fuel	Categorical variable: Petrol / Diesel / El + Diesel / El + Petrol where petrol = 0
timeregistered	Refers to the first time (exact date) the vehicle was registered in Norway
wheelbase	Categorical variable: Front wheel / Rear wheel / Four wheel drive. where front wheel = 0
horsepower	Horsepower of the enginge
cylindervolume	Indicates cylindervolume in Liters
co2emissions	Indicates CO2-emissions in grams per kilometer
bodytype	Categorical variable: SUV/5-door hatchback/stationwagon. Where SUV = 0
seats	Number of seats
doors	Number of doors
weight	Weight of vehicle in kilograms
colour	Colour dummies of vehicle where 0 is Beige and 1 is the respective colour
postalcode	4 digit postal code of where the posted vehicle is located
privateseller	Dummy variable where 0 is a retailer and 1 indicates a private seller
brand	Brand dummies where 0 is equal to Audi and 1 is the respective brand
age	Age indicates how many years old the vehicle is, where 1 is equal to 2021 and so forth
avgkm_year	Constructed average anual mileage in kilometer
Curve	Constructed variable meant to capture the curve effects predicted by prospect theory, see explanation in methodology chapter
Slope	Interaction term of a constructed dummy with 0 if avgkm_year is under the referance point and 1 if avgkm_year is above, multiplied by the transformed deviation curve.
kilometerover100k	Dummy equal to 1 if total car mileage is up to 100 000km, 0 otherwise
Kilometer2	Quadratic term kilometer
age2	Quadratic term age
enginetype	Dummy equal to 1 if engine type is diesel, 0 otherwise
enginetype2	Dummy equal to 1 if engine type is diesel and total car mileage is up to 100 000km, 0 otherwise
region	Categorical variable: Midt-Norge/Nord-norge/Sørlandet/Vestlandet/Østlandet. Where Midt-Norge = 0
horsepower2	Quadratic term of horsepower
transmission#c.kilometer	Interaction effect between transmission x kilometer
c.age#c.kilometer	Interaction effect between age x kilometer

In table 2, we can observe some aggregate statistics by car brand. It reveals quite big differences in averages of important explanatory variables. This will be useful to keep in mind in the analysis of their effects on prices.

Table 2: Overview of car brands and major variables

brand	average price	average modelyear	kilometer	horsepower
Citroen	123685.3129	2015.69	76974.60544	101.014
Hyundai	150418.4066	2015.15	88465.95604	122.033
Renault	158314.7755	2016.86	54681.34694	107.689
Opel	173276.1817	2015.75	80161.60847	130.034
Kia	178396.3939	2015.72	80768.49388	130.112
Seat	187283.0222	2018.34	73697.76667	126.211
Nissan	191738.2461	2015.29	92678.35433	132.506
Peugeot	194476.924	2016.17	79519.2	122.812
Ford	214722.6629	2016.21	83933.62263	140.281
Volkswagen	215195.1204	2015.79	98225.06941	151.784
Suzuki	219731.8023	2017.18	59392.27132	116.636
Toyota	236234.6613	2016.56	72764.924	138.215
Skoda	244992.8153	2016.39	95485.97709	145.981
Mazda	254239.4023	2016.47	80225.22095	154.723
Mitsubishi	264558.072	2016.41	85428.40216	182.658
Audi	280930.5047	2015.26	108640.3121	185.912
BMW	348765.486	2015.87	99230.76106	211.467
Mercedes-Benz	351636.9826	2016.013	99361.31157	214.326
Volvo	434958.4068	2016.88	89610.60518	269.129
Porsche	737979.7753	2015.54	96557.6367	344.895

Table 3 is a table of descriptive statistics of the numerical variables in our dataset. It shows that the average car in our dataset has a price of about NOK 277000, being a 2016 model and has driven 88000 kilometers.

Table 3: Descriptive statistics of numerical variables

Variable	Mean	(Std.dev.)	Min	Max
price	276971,8	180213,5	24380	2499900
modelyear	2016,161	2,6665	2011	2021
kilometer	88844,21	54429,15	1	569000
horsepower	175,922	85,3330	60	680
cylindervo~e	1,8057	0,4895	0,9	6.2
co2emissions	114,4786	39,9382	11	394
seats	5,0666	0,4232	4	7
doors	4,9640	0,1883	4	8
weight	1535,601	319,123	805	2780
postalcode	3924,999	2294,957	121	9990
privateseller	0,1993124	0,3995	0	1

Under is a correlation plot of our numerical variables. It shows that price is highly correlated with factors such as age (-0.58), horsepower (+0.81), weight (+0.73) and cylinder volume (+0.53).

Table 4: Correlation plot of numerical variables

	price	age	kilome~r	avgkm_~r	co2emi~s	cylind~e	doors	horsep~r	privat~r	seats	weight
price	1										
age	-0,58	1									
kilometer	-0,3786	0,7136	1								
avgkm_year	0,0998	-0,0375	0,6033	1							
co2emissions	-0,1391	0,4114	0,3654	0,0618	1						
cylindervo~e	0,5289	0,082	0,236	0,2396	0,265	1					
doors	-0,0713	0,0908	0,0421	-0,0556	-0,0511	-0,0331	1				
horsepower	0,807	-0,3189	-0,1274	0,1771	-0,2995	0,5774	-0,004	1			
privatesel~r	-0,1631	0,2723	0,2521	0,0611	0,0871	0,0424	0,0715	-0,0597	1		
seats	0,2851	-0,0856	-0,0005	0,0967	-0,0304	0,0956	0,0106	0,2313	-0,0259	1	
weight	0,7315	-0,1424	0,0947	0,2836	-0,1303	0,7262	-0,0321	0,8327	-0,0184	0,2905	1

4 Methodology

4.1 Empirical testing of prospect theory assertions

We start out our empirical studies using the proposed method of Betts & Taran (2007) "*Using curvilinear spline regression to empirically test relationships predicted by prospect theory*". They describe a six-step procedure outlined below.

1. Define a measure of utility corresponding to different levels of the variable under investigation (for example, the price people are willing to pay for a certain good)
2. Define reference points, for example average in its class.
3. Introduce a dummy variable *I* equal to 1 above the reference point and 0 below the reference point.
4. Apply cubic root functional transformation of reference deviation from chosen variable to model the shape of the value function as in prospect theory. This is the curve term.
5. Multiply the dummy variable *I* with the transformed deviation curve. This is the slope term, which captures the disproportionality between disutility of loss relative to the utility of gains.
6. Run regressions with both the curve and slope term as independent variables, with the expectation that the curve term will be significant and positive, and that the slope term will be negative.

We start out setting the same reference point as Prieto et al. (2014). They use yearly kilometers driven as the variable under investigation and sets the reference point at 15.000 km/year for diesel cars and 25.000 for petrol cars. This reference point is argued for in their article because it is deemed the standard benchmark a car usually drives per year from retailers, insurance companies and folk wisdom (Prieto et al. 2014). Thus, deviations from this benchmark should, according to the article, lead to different price reactions above and below this point due to the mechanisms described by PT.

Our hypotheses will be the following:

Hypothesis 1: Yearly mileage will have a decreasingly positive effect on price with yearly mileage above the reference point and an increasingly positive effect on price with yearly mileage below the reference point. (This is captured by a positive curve term)

Hypothesis 2: The increase in the relationship between yearly mileage and price when yearly mileage is below the reference point is greater than the decrease in the same relationship when yearly mileage is above the reference point. (This is captured by a negative slope term)

As Betts & Taran (2007) state clearly, there can be multiple basis for setting a reference point and different individuals can have different framing procedures. Therefore, one might expect to find weak but tangible statistical influence from a multitude of reference points. The plausible reference points they suggest that we will investigate, are as follows:

- Average odometer/year for all cars
- Average odometer/year for all cars, per model year
- Average odometer/year per respective car model
- Average odometer/year per specific car model, per year (e.g average for a volvo xc60 2019 model)

4.2 Methodological aspects of hedonic modeling in the used car market

When making a hedonic pricing model for used cars, it is useful to distinguish between explicit, defined characteristics of the vehicle and how that characteristic is transformed into utility for the consumer. Following Otha & Griliches (1976), we use the term physical variables for the former and performance variables for the latter. Examples of physical variables are horsepower, weight and length, while performance variables include acceleration, steering and real fuel economy. Some performance levels (f. ex. engine power and accommodation levels) are closely linked to physical attributes of the car (horsepower and automatic climate control). In this situation, the physical attribute is a good proxy for the performance variable which ultimately contributes to the utility the consumer derives from the car. Other performance variables, such as prestige and design differences, are not closely linked to physical attributes of the car and are therefore much harder to measure accurately in a hedonic model.

We assume that brand dummies will capture most of these hidden quality differences. But it is a challenge to describe how the relationship between brand-specific characteristics and price is, in a more detailed way than simply showing that brand effects exist. It is thus hard to separate between brand effects understood as perceived quality difference (goodwill/positioning effects) and brand effects understood as actual physical quality differences in the car. The small but many build quality differences are data points which we do not have access to. Both because an infinitely detailed objective description of a car is close to impossible, and because car specification categories that have been implemented on Finn are optional and somewhat limited. Since the list of measurable characteristics is never complete, there may be systematic differences across different brands in levels of the left-out variables, which can influence the accuracy of model estimations.

Following this omitted variable issue, it is also worth mentioning the special attention which the age and odometer value variable deserves. The model year can be thought of as measuring two main underlying attributes. It measures the model year in the sense that a newer car probably will be a better produced car – with ever-more technology, equipment, and safety attributes, only some of which we have data measuring. In this respect, it captures some omitted physical variables. The other main aspect is the age of the car as a quality indicator in the same way a high odometer value suggests a more worn-out car. An older, more driven car simply is more likely to be worn out and break down in different ways. Ideally, we would want to measure these effects separately, but it is no easy way of doing it. Rather, we can be mindful that age probably captures a lot of omitted physical and quality variables, and thus the coefficient of age should be interpreted with care. In the sense of measuring wear and tear, age and odometer value are best thought of as quality variables that affect the expected and actual quality of the physical characteristics the car consists of.

4.3 Deciding on functional form: Predictive power vs. determination of implicit prices

When deciding on a functional form, we start using the semi-logarithmic form used in Prieto et al. (2014) for comparison purposes. But beyond that, our mission is to describe the relationship between car characteristics and prices in the most accurate way possible. Most hedonic articles focus on choosing functional form based on the highest degree of predictive power - AKA getting the total price as close as possible to the correct one. But this criterion, as Sheppard (1997) points out, may not be the functional form which determines the implicit prices of attributes most accurately:

"For this objective, minimization of the squared predictive error may be inappropriate, and a model which fits the data well in this sense may be less satisfactory than another with less predictive power but more stable parameter estimates. " Sheppard (1997, p. 13).

Cropper, Deck and McConnell (1988) investigated this issue. They found that linear, loglinear and linear box cox transformation had the most stable coefficient estimations, depending on the nature of the data. In datasets with omitted variables issues, the semi-log form was the most stable. We decide on focusing on log-linear price models because of this.

4.4 Ask vs. transactional prices

Another methodological problem is that of the difference between ask - and transactional prices. Our data set consists of ask prices, which could potentially vary significantly from actual transactional prices. This could impact pricing estimations, although Kooreman and Haan (2006) claim that the two are "closely related, if not identical" in well-functioning car markets. In future research, it would definitely be an improvement to try to get a hold of transaction prices instead.

4.5 Model specifications and diagnostics

As we have stated earlier, we are going to build several models to test prospect theory and investigate pricing patterns in the used car market. The first model we build is as close to Prieto et al. (2014) as possible to be able to compare results.

Prieto model

$$\boldsymbol{Ln(\,P_i) = \beta_0 + \sum_{j=1}^{n} \beta_j X_{ij} + \mu_i}$$

Where *Pi* is the price of the *i* product, *n* is the number of characteristics for each respective car in the dataset, β_0 is the regression intercept, β_j is the regression coefficients for the characteristic *j* of product *i*, and μ_i is the error term. The remaining models are based on the Prieto model but include more variables which are argued for in the result section. To test the validity of the created models, we have conducted some regression diagnostics. The tests used are Ramsey reset to check for specification errors and Breusch-Pagan to test for heteroskedasticity (HC).

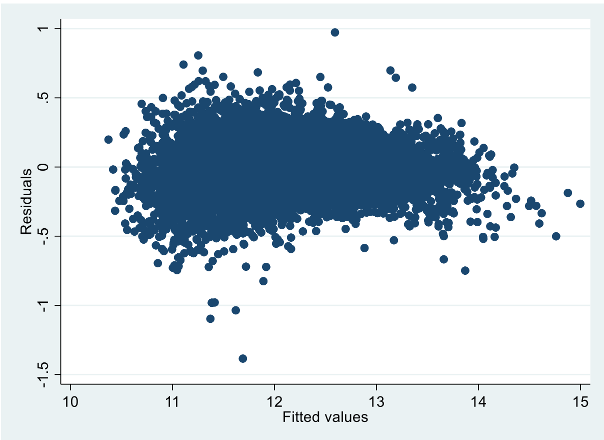
Table 5: Regression diagnostics

	Ramsey Reset	**Breusch-Pagan**
Model 1	1018.89	82.74
	0.0000	0.0000
Model 2	499.43	42.39
	0.0000	0.0000
Model 5	632.11	48.17
	0.0000	0,0000
Model 6a	475.51	1979.62
	0.0000	0.0000
Model 6b	451.95	1942.84
	0.0000	0.0000
Model 6c	492.34	1979.32
	0.0000	0.0000
Model 6d	493.29	1980.15
	0.0000	0.0000

The results of all Ramsey reset tests shows that we have some omitted variable issues, with p-values of 0.000. This is not surprising considering we know that we do not have all the data available to consumers on FINN.no in our models. As previously mentioned, we do not use equipment data nor text/image-based information on the ad which might give valuable information about the car in question. Omitted variables can impact the curve and slope terms via the effects discussed in the methodology chapter on the special attention which age and mileage deserve (since curve and slope are transformed variables of age and mileage). Thus, we need to have some skepticism about the coefficients of age, mileage, curve and slope.

The Bresusch-Pagan test presents F values of 0.0000 in all models, which tells us that the models exhibit heteroskedasticity. To deal with this, we run HC-standard error regressions to obtain more precise standard errors, where no variables changed significance status worth mentioning. We can also observe the cone shaped residuals in figure 1, showing that model 5 has more variance in its error terms for smaller fitted values. This pattern is similar for the other final models. We have a few suspected reasons why the RVF plot shows larger variability for lower priced cars. As mentioned earlier, the prices in the dataset are ask prices. This means that the seller specifies the price he wishes for the car he sells. One can imagine that for cheaper cars, the percentage difference in ask prices for similar cars are simply bigger than for more expensive cars. This is an inherent bigger variability in the price data for lower-end cars which would lead to a pattern akin to the one we observe in the *lnprice* residuals plot. The second reason we suspect is that of omitted variables and its bigger percentage effect on cheaper cars. For example, if two cars, one cheap and one expensive, have specified that winter tires are included in the deal. The absolute value effect of this extra equipment will be the same, but the percentage variability we observe when not accounting for these equipment dummies should be bigger in cheap cars. Thus, it is not all that surprising that the residuals are larger for cheaper cars.

Figure 1: residuals vs. fitted plot of model 5



5 Results

The results section is structured as followed: First, we replicate the method of Prieto et al. (2014) in the most accurate way possible using the data we possess. Afterwards we try to explain the process in creating a best possible general pricing model; We see value in adding more characteristics to predict the price of a vehicle than what Prieto et al. (2014) presents. Creating a better model will enable us to capture PT behavior more accurately. In the end we test whether other reference points could be better suited with our created model.

5.1 Model 1 – Replication of the Prieto model

The attempt to replicate the test of PT assertions by Prieto et al. (2014) is done by having a model specification as similar as possible to Prieto's model. The small differences between the Prieto model and our replication are the following: We have other and many more car models, body categories, some other color dummies, different geographical dummies (since we conduct our study in a different country) and finally our lack of seller type as an instrumental variable that Prieto has included. Seller type as an instrumental variable is not included in our model because we lack data on when the ad was posted on Finn, which they use as their instrumental input controlling for seller type in their two-stage least squares method. This could affect our results and we can therefore not claim to be perfectly identical to the Prieto model, but we still believe it is close enough to be worth comparing.

The results in our replication of Prieto's model (1) in table 5 show that the *curve* and *slope* terms are in fact consistent with their findings, in terms of a significant negative coefficient for the *slope* (-0.0086) and a significant positive coefficient for the *curve* (+0.0040). This indicates - at first glance - that prospect theoretical behavior in the secondhand car market in Norway could be present, using the same variables and assumptions as Prieto et al. (2014). However, we do believe that there exists other important characteristics that should be included to achieve a more accurate pricing model. For example, Prieto et al. (2014) has not included a mileage variable in their model. This seems very odd considering it is one of the most important variables in explaining used car prices, as many papers have shown (See Otha and Griliches (1976) for example). It seems particularly important to include mileage since the *curve* and *slope* terms are constructed transformations of mileage and model year. Thus, they are bound to have some specific relation with mileage. Adding the *kilometer* variable will therefore probably be a better specification of the model and separate the effects such that the curve and slope variables does not capture variance which in reality is explained by the *kilometer* variable.

Therefore, we should attempt to complete the model with more variables that we have available such as *kilometer, cylindervolume* and *co2-emissions*.

5.2 Model 2 – Adding more variables into the original model

Model 2 shows that insignificant and much smaller coefficients appear for the *curve* and *slope* terms (0.0002 for the *curve* and 0.0002 for the *slope*, not significant at 95% level). It seems that controlling for other variables diminishes the apparent effect of the *curve* and *slope* terms and shows their insignificance in explaining used car prices. By using enough variables to construct the price of a vehicle we show that it seems *curve* and *slope* terms are confounding variables, in which mileage probably is the real variable that influences both these terms and price itself. We also see that model 2 can explain much more of the variance in price, with an adjusted *R squared* of 0.9445 vs. 0.8025 in model 1.

5.3 Model 3 and 4 – linear and log linear general hedonic models

Model (3) and Model (4) are linear and semi log models respectively, with the same variables as model (2) except the *curve* and *slope* term. We observe that the log linear model seems to be able to explain more of the variance in the data, with an *R squared* of 0.94 vs 0.90 for the linear model. We can also see from the residuals vs. fitted plot in the appendix that the linear model seems to be wrongly specified, with a skewed and u-shaped residuals form, vs. the more fan-shaped residuals for the log-linear model. Since model (4) is identical to model (2) expect for the insignificant *curve* and *slope* terms that we removed in model (4), it is not surprising that we get coefficients that are close to identical with model (2) and the same *R squared* of 0.94 for both models. This leads to model (4) being the most satisfying pricing model for the time being.

5.4 Model 5 – Interaction terms

Although model (4) can be considered a reasonably good pricing model, it is important to keep in mind that some interactions between different characteristics in vehicles are probably present. Earlier research has for example indicated synergy effects between the age of a car and its mileage, or between the vehicle's transmission type and mileage (Estelami & Raymundo, 2012). The rationale for the age-kilometer relationship is as follows: older cars are more susceptible to wear and tear, and therefore every kilometer has more potential in doing damage to the older vehicle. In any case, our findings confirm these earlier studies. We read from the *age X kilometer* variable in model (5) that a kilometer has an extra negative effect of -3.3*10^-8 on lnprice for every year older the car is. Hypothetically speaking, a car that has driven 100.000 kilometers and 10 years old will thus be 3.3% cheaper than a 0 year old car that has driven 100.000 kilometers, from the effect of the interaction term. We also read that an automatic car depreciates less per kilometer than manual cars, with an interaction coefficient with kilometer of 0.00000106. Furthermore, we included quadratic forms of age and kilometer to investigate if there are any nonlinear elements to these variables in explaining price. We can see that *age2* has a significant coefficient of -0.0047, and the linear *age* variable -0.0536. This means that *age* has an increasingly large effect on price of vehicles the older the car gets. With *kilometer,* the *kilometer2* coefficient is -4.47*10^(-13) and insignificant, while the linear coefficient is -0.00000322 and significant. This means that kilometer has a consistent linear effect on *lnprice*, where a car that has driven for example 10.000 kilometers more can be expected to be 3.22% cheaper, all else held equal.

5.5 Model 6 – Testing other reference points

Having decided on a reasonable model specification for the general hedonic model, we further test other reference points to check whether these make more sense. We have tested the following reference points:

- Model 6a; average yearly mileage per model per year.
- Model 6b; average yearly mileage per model.
- Model 6c; average yearly mileage of all cars.
- Model 6d; average yearly mileage of all cars per year.

As we can see in models 6a,b,c,d, the coefficients for the *curve* and *slope* terms for all models are significant. They all consist of positive values for the *curve* term and negative values for the *slope* term. This implies that there could exist PT behavior when using other reference point, using the same definition for the *curve* and *slope* terms as Prieto et al. (2014).

In clear text, the significant curve coefficients for models 6a-d show that positive reference deviations have a decreasingly positive effect on price per kilometer over the reference value. The *slope* coefficients show that the *curve* is steeper below the reference point. This means that cars with a positive reference deviation are cheaper than what a linear mileage effect would assume. It also means the opposite; that cars with large annual mileages in comparison with their reference value, are relatively more expensive than a linear effect, everything else held equal.

Nevertheless, it should be mentioned that only model 6a and 6b have *adjusted R squared* values larger than model 5 without curve and slope terms. So, while model 6c and 6d have significant *curve* and *slope* terms, they do not seem to be able to explain more of the variance.

Table 6: Regression results

	Model 1	Model 2	Model 5	Model 6a	Model 6b	Model 6c	Model 6d
constant	12.42***	10.76***	10,65***	10.68***	10.72***	10.66***	10.66***
R2	0.8027	0.9447	0,9495	0.9497	0.9500	0.9495	0.9495
adj R2	0.8025	0.9445	0,9494	0.9496	0.9499	0.9494	0.9494
curve	0.0040***	0.0002		0.0013***	0.0027***	0.0009***	0.0010***
slope	-0.0086***	0.0002		-0.0005	-0.0015***	-0.0012***	-0.0015***
kilometerover100k	-0.0001						
enginetype2	-0.0661***						
horsepower2	7.32e-06***						
enginetype	0.2653***						
region_n							
Midt-Norge	0.0667***	0.04378***	0.0407***	0.0412***	0.0418***	0.0410***	0.0410***
Nord-Norge	0.1098***	0.0683***	0.0701***	0.0696***	0.0691***	0.0696***	0.0696***
Sørlandet	-0.0054	0.0057	0.0044	0.0043	0.0042	0.0042	0.0042
Vestlandet	0.0310***	0.0241***	0.0230***	0.0225***	0.0222***	0.0227***	0.0227***
bodytype_n							
Hatchback 5-door	-0.3335***	-0.0549***	-0.0511***	-0.0504***	-0.0497***	-0.0510***	-0.0509***
Stationwagon	-0.1665***	-0.0358***	-0.0338***	-0.0379***	-0.0417***	-0.0338***	-0.0338***
age2	-0.0112***		-0.0047***	-0.0041***	-0.0035***	-0.0044***	-0.0044***
age		-0.1182***	-0.0536***	-0.0662***	-0.0778***	-0.0575***	-0.0575***
co2emissions		0.0023***	0.0027***	0.0027***	0.0027***	0.0027***	0.0028***
cylindervolume		0.0980***	0.0722***	0.0733***	0.0737***	0.0723***	0.0724***
doors		-0.0125**	-0.0150***	-0.0134**	-0.0141**	-0.0148**	-0.0148**
horsepower		0.0011***	0.0011***	0.0011***	0.0012***	0.0011***	0.0012***
kilometer		-2.63e-06***	-3.22E-6***	-2.47E-06***	-1.70e-06***	-2.99e-06***	-3.00E-06***
privateseller		-0.0428***	-0.0426***	-0.0431***	-0.0434***	-0.0426***	-0.0426***
seats		0.0558***	0.0535***	0.0528***	0.0526***	0.0534***	0.0535***
weight		0.00073***	0.0007***	0.0007***	0.0007***	0.0007***	0.0008***
wheelbase_n							
Four-wheel drive		0.0891***	0,0681***	0.0689***	0.0700***	0.0685***	0.0687***
Rear-wheel drive		0.1073***	0,1028***	0.1006***	0.0970***	0.1027***	0.1027***
transmission_n							
Automatic		0.1467***	0,0249***	0.0236***	0.02622***	.0244***	0.0243***
fuel_n							
Diesel		0.2363***	0,2159***	0.2122***	0.2114***	0.2165***	0.2164***
El + Petrol		0.0889***	0,0879***	0.0863***	0.0840***	0.0884***	0.0885***
Petrol		0.2007***	0,1527***	0.1512***	0.1512***	0.1531***	0.1537***
c.age#c.kilometer			-3.30E-08***	-4.97E-08***	-7.82e-08***	-5.20e-08***	-5.26E-08***
transmission_n#c.kilometer							
Automatic			1.06E-06***	-4.97E-08***	-7.82e-08***	-5.20e-08***	-5.26E-08***

*Red markings indicate insignificant p values at 5% level. * = 10% level, ** = 5% level, *** = 1% level. Car brand and color dummies for all models can be found in the appendix to save space*

5.6 Other findings

In the spirit of searching for pricing irregularities in comparison to what standard utility theory posits, we supplement our study by using the same research questions as Kooreman & Han (2006). We investigate whether a car that has crossed the 100.000km odometer threshold has a significant drop in price. This should not be the case if the relationship between kilometer value and price is assumed to be continuous, which makes sense since the underlying wear and tear effect of driving a car more is reasonable to think of as a stable force. But it is a famous effect among car enthusiasts and therefore worth testing (Kooreman & Han, 2006). We also investigate whether age in quarters has a significant impact on price. Kooreman & Han found that only age in years had a significant effect on price, which should not be the case from a standard utilitarian perspective where age also should have a continuous effect on the quality of the vehicle, such that quarterly age should be a relevant factor.

In table 8 and figure 4 in the appendix, we can see that we do not find a significant drop in the price of vehicles that have passed the 100.000 km threshold. This is consistent with standard utilitarianism. Also, quarterly ages do not seem to be significantly affecting price – only age in years. This is still the case after controlling for seasonal effects. This contradicts standard utility theory.

6 Discussion

As shown in the results section, we do not seem to be able to find evidence for prospect theory effects in our data. We do find statistically significant curve and slope terms using Prieto's variables and Betts & Taran's suggested method. Controlling for other variables in further models removed the effects of these terms. We also investigated other reference points and found some indications of different price reactions above and below these points. But we do not want to hastily conclude that this is evidence in favor of prospect theory as such. We have five main reasons as to why we hesitate with concluding that these curve and slope terms are evidence for PT. They all share the theme of suspecting that it simply might be wrong – or at least very challenging - to try to apply PT in complex purchasing decisions such as the used car market – At least in the way Betts & Taran (2007) and Prieto et al. (2014) have proceeded. The mismatch between the domain of prospect theory and the application in the used car market is summed up in the table below.

Classical PT application aspects	Prieto application
(1) Individual level measurements of risk attitudes and estimates of value functions	Market level measurement of pricing structure and claims of discovering implicit value functions
(2) Single payoff dimension	Multitude of payoff dimensions
(3) Two choice options	Thousands of choice options
(4) One payoff dimension with one reference point associated with	Multiple payoff dimensions with one dimension chosen as the framing variable in which reference points are claimed to be relevant
(5) Explicit risks entailed with choice options	Unclear and unspecified risks involved

1: A methodological advantage of many PT laboratory experiments is using individual level research methods instead of market level data. This enables having information on individual level measurements of risk attitudes and estimates of value functions. In Baillon et al. (2020) they are able to estimate consistent heterogenous reference point tendencies for different individuals over time. For example, some individuals may use the "average expected value" as a reference points, while others seem to use the "minimax principle", which entails defining the reference points in relation to the option in which you can lose the least amount. They show how reference points play a big role, but indeed through different reference point categories for different individuals. It may be that individuals employ a wide variety of reference points in a complex purchase such as the used car case, but that these different reference points pull in different directions and thus null out the aggregate effect. Or it may be that there are no such effects at all. In any case, the methodological approach suggested by Betts & Taran (2007) with market level aggregate measurements does not seem a good tool if one wants to find solid evidence of PT behavior in complex purchasing decisions. Since one can never be sure of what heuristics the individual choice makers have employed in their purchasing considerations.

2: Most of PT literature has focused on choices with payoffs along one dimension (e.g money, life years, see for example van Osch et al. (2006)). Only a few articles have attempted to empirically investigate PT in choices with several payoff dimensions (See Kemel & Paraschiv, 2013). A car, although its primary "payoff" is its transportation ability, can be said to have hundreds if not an undefined amount of payoff dimensions - if thought of in the hedonic framework where goods consist of all the characteristics that produce utility. Therefore, we struggle to see how yearly mileage reference points should be suspected to produce the significant slope change in price which PT posits. It does not seem to make sense intuitively that this one factor should be that influential in pricing of a vehicle. Nor does the data indicate it (in that we show that most of the features we have in our dataset are important pricing factors), and neither does the current PT framework allow for such an effect (since the theory in its original form assumes payoff from one factor exclusively).

3: Most PT applications investigate choices with two options. In the used car market, consumers have thousands of options, and thus the choice process is necessarily more complicated and considerate – a high involvement decision. A lot of literature exists in explaining how consumers simplify the search process in such choices. For example, the bounded rationality model by Herbert Simon in which consumers are described as satisfiers instead of utility maximizers (Simon, 1955), or the heuristics literature which explain how shoppers create rule of thumbs in finding the right product for them (Benartzi & Thaler, 2007), (Cripps & Meyer, 1994). In marketing, reference price and price-quality segments are common terms for explaining consumer behavior in high-involvement decisions (Baltas & Saridakis, 2009). One can also imagine that cars with different yearly mileages simply have different depreciation rates, such that the standard theory of utility also can be a plausible explanation to the price curvature. The point of these examples is to illustrate how the choice architecture of the used car market necessarily complicates the analysis. There are clearly a lot of factors that is shown to influence how consumers make their choices in complicated situations. This should in our opinion raise suspicion as to whether it makes sense to argue specifically for the effects of prospect theoretic framing related to observed curvature in the used car market, or any other complex choice.

4: Most PT applications revolve around situations in which there is a singular dimension that choice makers will make related reference points to. Since a used car purchase involves a lot of payoff dimensions, it does not seem obvious which payoff dimension the consumer will anchor their reference points to. It may be that consumers do not have reference points in multiple payoff situations, or that they have several reference points which individually have weaker effects on price - or as Prieto et al. (2014) assumes – a single reference point relating to one of the variables under consideration. The last one does not seem particularly probable when thought of in the hedonic framework where consumers are assumed to care about all features of a car. In any case, simply assuming one of the variables and a reference point relating to that variable seems reckless.

5: Classical PT choice structures include explicit risks associated with each option. It might help with an example to illustrate how classical PT situations does not seem to map onto the used car case with respect to risks. First, using the example Kahneman & Tversky used in their seminal 1979 paper to show how consumers become risk seeking in risky choices with a loss frame: Imagine choice 1 and 2, where you have given probabilities of getting a certain payoff. The structure of the nomenclature is as such:

Option name (payoff value, probability; other payoff value, probability) [percentage of option chosen in experiment]

$$Choice\ 1: A(6000, 0.25)[18]\ or\ B(4000, 0.25; 2000, 0.25)[82]$$
$$Choice\ 2: A(-6000, 0.25)[70]\ or\ B(-4000, 0.25; -2000, 0.25)[30]$$

In choice 1, the choice is made in a gain frame – all outcomes are gains with respect to the given reference point. The expected value of the two options in choice 1 are identical at (6000*0.25 = (4000*0.25+2000*0.25)=1500, but because of risk averseness, the authors claim that option B (4000,0.25;2000,0.25) is the preferred one – as can be seen by the much larger percentage of the experiment participants choosing the option (82% vs 18% for option B vs A in choice 1). It is a choice with less variance and higher probabilities of winning something.

In choice 2, the payoffs are identical except for being negative instead of positive. Now the majority preferred option has been flipped with 70% of participants choosing option A. This is a riskier choice in the sense that the maximum loss is bigger, but there is at the same time a lower probability of losing something. This is the effect which Kahneman & Tversky claims is the underlying reason why people become risk seeking in loss frames – losses loom larger than gains, in a disproportional relation to the absolute amount of the loss, with a skew towards weighting lower losses more than bigger losses.

The key theoretical point to take away from this example is that people become *risk seeking* in loss frames – whereas standard utility theory claims that people are *risk averse* (or risk neutral) in all choices. But does it make sense that this kind of behavior maps onto the used car case? Now imagine a simplified similar example applied in the used car market, in the spirit of Prieto et al. (2014): The consumer has a choice between two cars with different levels of annual miles driven. The first choice is between a car that has driven 5.000 kilometers per year and a car that has driven 10.000 kilometers per year. With the reference point Prieto et al. (2014) suggests at 15.000km/year, these values are transformed into *reference deviations* of

(15.000 – 5.000) = 10.000km/year and

(15.000 – 10.000) = 5.000 km/year

Since these are positive deviations, Prieto et al. (2014) claims this choice is made in a gain frame. Flipping these deviations by imagining two other cars who has driven 25.000 and 20.000 yearly kilometers, we get the same choice in a loss frame, with negative reference deviations of

(15.000 – 25.000) = - 10.000km/year and

(15.000 – 20.000) = -5.000 km/year

Now imagine the consumer has these two choices between two cars to purchase:

$$Choice\ 1: A(5000, ?)\ or\ B(10000\ , ?)$$
$$Choice\ 2: A(-5000, ?)\ or\ B(-10000, ?)$$

We have put down question marks to highlight that the consumer does not know the risk he is facing when purchasing a car – at the most he has some idea about the risk structure of different brands (since it is known that different brands have better or worse reliability, for example). It is inherently an uncertain choice situation, but without stated risks, it becomes harder to fit the used car example within the PT paradigm, since risk is a key factor in the PT framework.

Even if we find evidence for curvature in accordance with prospect theory, we do not think this should be understood too quickly as evidence for PT being the causal mechanism bringing about this pricing curvature. It might be other factors at play which lead to the same kind of curvature one would expect from PT. Maybe other existing theories from other fields such as marketing can be better explanations. For example, there is an extant literature on reference prices and price-quality segments which also deal with references, expectations and more – but not necessarily in the context of risky choices such as PT does. But at the same time, we believe our paper can be a valuable first pass at an attempt to empirically test PT in complex decisions, which will hopefully inspire others to create more robust frameworks for the framing of decisions in the future.

To wrap up our discussion on PT, we want to mention some arguments in defense of Prieto's method. Mileage and car age are unique variables in the sense that they are quality indicators which affect the utility of all other car characteristics, because of wear and tear. So, if one *were* to test PT in car purchases, it makes some sense to test for those variables since they are variables which in some respect influence all characteristics of the car.

One can also - for the sake of imagination - imagine that PT is still valid in multi-dimensional choices, just with a less severe impact on prices per dimension**.** In that case, maybe the effect is so small for each attribute's loss and gain frames that it becomes hard to measure. In this case, conducting the study with transactional prices instead of ask prices may be decisive, since high accuracy is required to capture such small effects. Or it might be the case that the lack of an obvious reference point leads to individuals employing different ones. In this case, individuals may have powerful gain and loss effects, but the aggregate average effect might amount to nothing as discussed in point 1 in the discussion. Maybe it can be more fruitful in future studies with a research design that follows the same individuals over time, choosing between numerous vehicles, to get a better insight in individual choice patterns and associated reference points.

7 Conclusion

This article aimed to find evidence of pricing curvature in line with prospect theoretic assertions in the used car market using a hedonic pricing model. Trying to replicate Prieto et al (2014), we find evidence using their model specification. However, controlling for variables that other literature considers as important (*odometer value*, *cylinder volume* etc.), the effect of their suggested reference point is insignificant. We do find indications of other reference points being more able to explain pricing variation. In particular, deviations from average yearly mileages per respective car model seems to be the strongest reference point predictor. But these effects are still relatively weak. We conclude that the method proposed by Betts & Taran (2007) and used by Prieto et al. (2014) is not easily linked to the prospect theoretic framework. That is because it seems hard to convincingly establish a causal relation between mileage reference points and the supposed effects of the theory in consumer choices. A complex purchasing decision such as a used car purchase varies across a multitude pricing factors, contains a hard-to-quantify level of risk, and does not contain any obvious reference points in which consumers anchor their choice to. Not having access to individual level choice data and relying on ask prices in the marketplace weakens the ability to search for these supposed reference points. In sum, these factors should dampen hopes of asserting evidence for prospect theoretic effects in the used car market using factors such as yearly mileage.

With respect to the general hedonic model, we presented a few other findings worth mentioning. We find evidence for different effects of mileage on price depending on the transmission of the car, where an automatic car seems to depreciate less in value per kilometer than a manual car. Also, an older car is influenced more by mileage than a newer car, with respect to price depreciation. We do not find evidence for a significant drop off in prices after the 100.000 km threshold, that Kooreman & Han (2006) has shown earlier. We do find evidence of cars only depreciating in value from age in years – not at a higher fidelity such as quarters or months. Our findings may be distorted by the fact that we rely on ask prices instead of transactional prices. Therefore, in further research it will be beneficial to apply the latter in terms of precision of the hedonic parameter estimations.

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9 Appendix

Figure 3: Residual vs fitted plot model 3 and 4

Table 7: Full view of the remaining variables for the presented models (1 - 6d) in the result section. These are the tested brands and colors

	Model 1	Model 2	Model 5	Model 6a	Model 6b	Model 6c	Model 6d
colour_n							
Black	0.1246***	0.0238**	0.0251***	0.0250**	0.0254**	0.0251**	0.0252**
Blue	0.0958***	0.0329***	0.0358***	0.0360***	0.0360***	0.0359***	0.0359***
Bronze	0.1157*	0.0480	0.0364	0.0389	0.0384	0.0372	0.0371
Brown	0.0657***	0.0285**	0.0241***	0.0234**	0.0238**	0.0241**	0.0241**
Fiolett	-0.2488*	-0.1884**	-0.1447***	-0.1450**	-0.1436*	-0.1438*	-0.1438*
Green	0.0359	0.0422**	0.0496**	0.0474***	0.0499***	0.0493***	0.0494***
Grey	0.1104***	0.0350***	0.0357***	0.0351***	0.0356***	0.0356***	0.0356***
Orange	-0.0850**	-0.0703***	-0.0460***	-0.0453**	-0.0464**	-0.0460**	-0.0458**
Purple	0.0153	0.0928*	0.1086**	0.1062**	0.1086**	0.1093**	0.1093**
Red	0.0406*	0.0249**	0.0254***	0.0259**	0.0260**	0.0255**	0.0256**
Rosa	-0.3874**	-0.1655*	-0.1769***	-0.1681**	-0.1728**	-0.1767**	-0.1774**
Silver	0.0680***	0.0013	0.0043***	0.0047	0.0046	0.0043	0.0043
Turquoise	0.2841	-0.0680	-0.0775	-0.0759	-0.0776	-0.0752	-0.0747
White	0.0976***	0.0451***	0.0444***	0.0440***	0.0444***	0.0442***	0.0442***
Yellow	0.1369***	0.0721***	0.0786***	0.0774***	0.0791***	0.0785***	0.0787***
brand_n							
Audi		0.2528***	0.2523***	0.2469***	0.2498***	0.2522***	0.2521***
BMW		0.2193***	0.2265***	0.2250***	0.2261***	0.2263***	0.2263***
Ford		0.0847***	0.0812***	0.0802***	0.0808***	0.0811***	0.0810***
Hyundai		0.0109	0.0136	0.0139	0.0149	0.0135	0.0134
Kia		0.0804***	0.0783***	0.0810***	0.0798***	0.0784***	0.0782***
Mazda		0.0905***	0.1082***	0.1055***	0.1074***	0.1081***	0.1080***
Mercedes-Benz		0.2628***	0.2594***	0.2558***	0.2582***	0.2591***	0.2591***
Mitsubishi		0.0653***	0.0889***	0.0857***	0.0868***	0.0888***	0.0887***
Nissan		0.1121***	0.1026***	0.1036***	0.1033***	0.1023***	0.1023***
Opel		0.0254**	0.0284***	0.0343***	0.0317***	0.0282***	0.0281***
Peugeot		0.0889***	0.1043***	0.1027***	0.1040***	0.1044***	0.1044***
Porsche		0.4868***	0.4842***	0.4957***	0.4896***	0.4837***	0.4837***
Renault		0.0007	-0.0208	-0.0086	-0.0145	-0.0199	-0.0197
Seat		0.0487**	0.0695***	0.0466**	0.0575***	0.0723***	0.0722***
Skoda		0.1417***	0.1529***	0.1379***	0.1467***	0.1531***	0.1531***
Suzuki		0.2460***	0.2585***	0.2544***	0.2564***	0.2583***	0.2582***
Toyota		0.2361***	0.2421***	0.2433***	0.2426***	0.2422***	0.2421***
Volkswagen		0.1604***	0.1628***	0.1540***	0.1588***	0.1628***	0.1628***
Volvo		0.2249***	0.2321***	0.2253***	0.2290***	0.2324***	0.2324***

Table 8: Replication of Kooreman & Han (2006) regression.

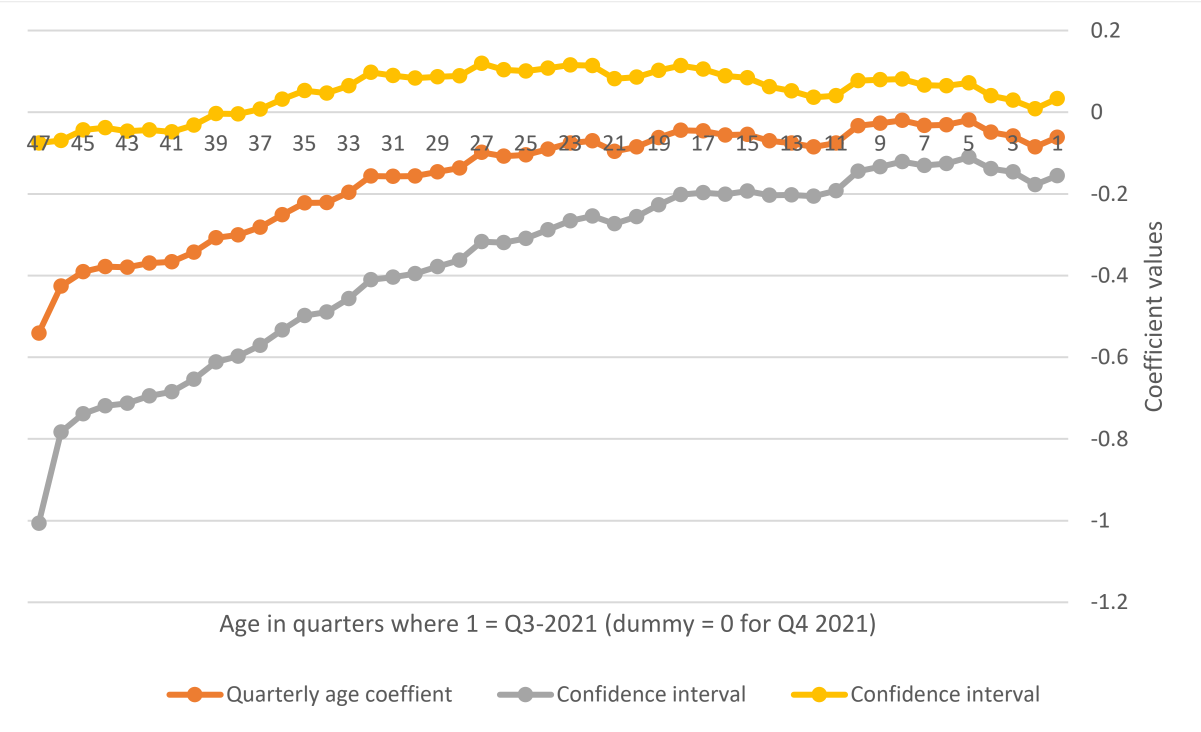
Source	SS	df	MS			
				Number of obs	=	20,651
				F(107, 20543)	=	3588.63
Model	8403.8641	107	78.540786	Prob > F	=	0.0000
Residual	449.604357	20,543	.021886013	R-squared	=	0.9492
				Adj R-squared	=	0.9490
Total	8853.46845	20,650	.428739392	Root MSE	=	.14794

lnprice	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
age	-.0801079	.0020808	-38.50	0.000	-.0841864	-.0760294
kilometer	-2.79e-06	3.90e-08	-71.44	0.000	-2.86e-06	-2.71e-06
kilometerover100k	.0048957	.0039537	1.24	0.216	-.0028539	.0126453
monthly_age	-.000369	.0012828	-0.29	0.774	-.0028834	.0021454
co2emissions	.0028522	.0000672	42.44	0.000	.0027204	.0029839
cylindervolume	.0695543	.005405	12.87	0.000	.0589601	.0801484
doors	-.0136658	.0058963	-2.32	0.020	-.0252231	-.0021085
horsepower	.0011598	.0000352	32.92	0.000	.0010908	.0012289
privateseller	-.0534669	.0027804	-19.23	0.000	-.0589168	-.048017
seats	.0524442	.0027677	18.95	0.000	.0470192	.0578692
weight	.0007621	.0000108	70.49	0.000	.0007409	.0007833
wheelbase_n						
Four-wheel drive	.0740402	.0037453	19.77	0.000	.0666992	.0813813
Rear-wheel drive	.1056542	.0075162	14.06	0.000	.0909218	.1203865
bodytype_n						
Hatchback 5-door	-.0468951	.0037698	-12.44	0.000	-.0542842	-.039506
Stationwagon	-.0365408	.00303	-12.06	0.000	-.0424799	-.0306017
brand_n						
Audi	.2556995	.0102348	24.98	0.000	.2356385	.2757605
BMW	.2262701	.0103346	21.89	0.000	.2060135	.2465266
Ford	.0784433	.0100253	7.82	0.000	.0587929	.0980936
Hyundai	.0160963	.0120902	1.33	0.183	-.0076015	.0397941
Kia	.0764153	.0114429	6.68	0.000	.0539862	.0988443
Mazda	.0907851	.0109263	8.31	0.000	.0693687	.1122014
Mercedes-Benz	.2617712	.0106301	24.63	0.000	.2409354	.2826069
Mitsubishi	.0818437	.011573	7.07	0.000	.0591597	.1045277
Nissan	.0895042	.0117226	7.64	0.000	.066527	.1124815
Opel	.0217412	.011222	1.94	0.053	-.0002548	.0437372
Peugeot	.0923781	.0105707	8.74	0.000	.0716587	.1130976
Porsche	.4896611	.014146	34.61	0.000	.4619337	.5173884
Renault	-.0081682	.0142062	-0.57	0.565	-.0360135	.0196771
Seat	.0654315	.018761	3.49	0.000	.0286585	.1022046
Skoda	.1566356	.0102846	15.23	0.000	.136477	.1767942
Suzuki	.2494057	.0118431	21.06	0.000	.2261924	.2726191
Toyota	.227236	.0105008	21.64	0.000	.2066536	.2478184
Volkswagen	.1667007	.0098535	16.92	0.000	.1473871	.1860143
Volvo	.2411993	.010174	23.71	0.000	.2212575	.2611411
transmission_n						
Automatic	.1324492	.0031523	42.02	0.000	.1262705	.1386278
fuel_n						
Diesel	.2115239	.0119003	17.77	0.000	.1881984	.2348494
El + Petrol	.0891227	.0109857	8.11	0.000	.0675899	.1106555
Petrol	.1515384	.0129556	11.70	0.000	.1261444	.1769323
region_n						
Midt-Norge	.0389626	.0039757	9.80	0.000	.0311699	.0467552
Nord-Norge	.0645848	.0043021	15.01	0.000	.0561522	.0730173
Sørlandet	.0036895	.004049	0.91	0.362	-.0042468	.0116258
Vestlandet	.0222321	.0026537	8.38	0.000	.0170306	.0274336
colour_n						
Black	.0244463	.011003	2.22	0.026	.0028796	.046013
Blue	.0362944	.0113472	3.20	0.001	.0140529	.0585359
Bronze	.0509035	.0327685	1.55	0.120	-.0133254	.1151324
Brown	.0249406	.0119951	2.08	0.038	.0014292	.048452
Fiolett	-.1781211	.0750235	-2.37	0.018	-.3251732	-.031069
Green	.0458873	.0184144	2.49	0.013	.0097935	.081981
Grey	.0351959	.0109959	3.20	0.001	.013643	.0567488
Orange	-.0546659	.0202242	-2.70	0.007	-.094307	-.0150248
Purple	.118298	.0482651	2.45	0.014	.0236945	.2129015
Red	.0267089	.0116206	2.30	0.022	.0039316	.0494862
Rosa	-.1558754	.0864133	-1.80	0.071	-.3252523	.0135015
Silver	.0028563	.0112726	0.25	0.800	-.0192388	.0249514
Turquoise	-.1228979	.1485065	-0.83	0.408	-.4139825	.1681867
White	.0420117	.0111445	3.77	0.000	.0201676	.0638558
Yellow	.078086	.0242837	3.22	0.001	.0304879	.125684
q						
2	-.0021246	.0029374	-0.72	0.469	-.0078821	.0036328
3	.0018255	.0029277	0.62	0.533	-.0039131	.0075641
4	-.0005967	.0029467	-0.20	0.840	-.0063725	.0051791
quarterly_age						

The *kilometerover100k* variable in the regression above suggests that cars do not have a marked drop in price when the odometer value rises above 100.000, as Kooreman & Han found in their paper.

The figure under shows quarterly age dummies from the regression above (they are cut out of the regression table because of lack of space on the page), which shows that most quarters have an insignificant effect on price compared to Q4 2021, our newest quarter. This indicates that consumers only value age in years. The dummies below are controlled for by seasonal dummies q2,3 and 4, which are also insignificant. This suggests that the season in which a car is born also does not have an effect on price. Last but not least, the monthly age factor is insignificant as well. In total, this suggests that vehicles are only priced in years.

Figure 4: Quarterly age-price dummies



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