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Investing in cars and the portfolio diversification gains.

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Abstract

In this paper, the investment performance of (classic) cars and the diversification gains on diversified investment portfolios is analysed. This paper will be the first to investigate the portfolio diversification gains for the (classic) car market. The study is based on a dataset comprising more than 25.000 cars built between 1947 and 2019. The data is gathered from auction results between 2002 and 2019. Multiple price indices are constructed to analyse the investment performance of (classic) cars using a hedonic pricing methodology. For the whole sample, the return between 2002 and 2019 was 1.46%, with a standard deviation (risk) of 10.08%.

After the investment performance is calculated, several investment portfolios are constructed based on financial assets and cars. By using the Risk-Adjusted Performance measure proposed by Modigliani and Modigliani (1997), the return of the various portfolios can be compared for the same level of risk. It is found that cars do have diversification gains on an already diversified portfolio. The portfolio with makes (cars from American, Italian, British, German, French and Japanese make) and the portfolio with all the risky assets outperform the portfolio without cars by 0.73% and 1.08% respectively, for the same level of risk. Thus, by adding cars to a financial asset portfolio, it is possible to achieve higher returns for the same level of risk.

Although positive returns and diversification gains are found, it must be noted that the costs associated with investing in cars are not included in this study. To investigate the investment performance and diversification gains including these costs, additional research is required.

Introduction

Nowadays, news articles containing car manufacturers complaining about investors become more common. It even comes to the point where companies are taking action to make sure their cars are used and driven, instead of being held in a garage as an investment object. Ford made their customers who wanted the new $450.000 Ford GT convince them that they would drive the car and hold it for at least a specified amount of time before selling it, before they were allowed to buy it.[1] Porsche GT boss Andreas Preuninger has a very clear opinion. He said: "I do not like this business of people buying our cars to make money on them. That was never our intention. The purpose of limiting a car is not for it to gain value. We do not want to be laying money on each car's roof when they run out of the factory". He goes even further when he said: "If you are flipping cars, then I think it is understandable that you will not get on the list for the next car if we have more demand than supply. It is not a punishment but a strategy: to supply the cars to the customers who will really use them. I think that is just fair."[2]

Investors seem to have noticed the car market as an alternative to the traditional financial asset classes, like equities and bonds. This was fuelled by David Gooding, president of Gooding & Company, hosts of the prestigious Pebble Beach Concours d'Elegance auction, by saying "If you bought an exceptional example [classic car], you most likely will only gain value over the next 10 years."[3] Next to these enormous amounts of money paid for classic cars, the Historic Automobile Group International (HAGI), reported that the market for collector cars grew by more than 200% between 2009 and 2016 (Martin, 2016). This was supported by Jens Berner, vintage car expert at Südwestbank AG: "After the financial crisis, requests for alternative investments such as art, wine or classic cars had risen sharply".[4]

Car auctions experienced a large jump in total sale prices between 2016 and 2017, increasing from $329.040.445 in 2016, to $540.277.825 in 2017, an increase of almost 65%. Thereby becoming a market with over $500 million worth of sales over the last two years. A few cars really stand out due to their auction prices. There were four cars auctioned for more than 20 million US Dollars in 2017 and 2018, two Ferraris and two Aston Martins. A 1956 Ferrari 290 MM racer sold for a little more than $22.000.000 and a 1962 Ferrari 250 GTO Series II Berlinetta sold for a breath-taking $48.405.000.[5][6] As of today, this is the highest price ever paid for a car at an auction. However, it is not the highest price paid for a car in general. It is believed that David MacNeil paid $70.000.000 for a 1963 Ferrari 250 GTO in a private sale.[7]

Although the return of investing in classic cars was studied before (Laurs & Renneboog, 2019; Martin, 2016), there are no studies regarding the potential for cars to provide a diversification gain to an already diversified portfolio. An overview of other studies regarding investments in alternative assets can be found in the literature review. In this paper, the returns on classic cars are calculated using a database consisting of more than 25.000 records of auctioned cars. Next to that, portfolios are constructed using the Modern Portfolio theory first introduced by Markowitz (Markowitz, 1952). After the portfolios are formed, the performance measure proposed by Modigliani and Modigliani is used to evaluate the performance of different portfolios and to compare the performance of these portfolios (Modigliani & Modigliani, 1997).

[1] https://www.wsj.com/articles/ford-wants-buyers-to-actually-drive-the-new-gt-1460581467

[2] https://www.thedrive.com/sheetmetal/10725/porsche-gt-boss-cracking-down-on-people-who-flip-his-cars

[3] https://www.christiesrealestate.com/blog/how-to-invest-in-a-classic-car/

[4] https://www.bloomberg.com/news/articles/2018-07-09/vintage-porsches-683-gain-fuels-returns-in-carmakers-homeland

[5] https://www.topgear.com/car-news/motorsport/ferrari-290mm-racer-just-sold-22m

[6] https://www.cnbc.com/2018/08/27/most-expensive-car-ever-sold-at-auction-fetches-48-million.html

[7] https://edition.cnn.com/style/article/ferrari-250-gto-1963-record-sale/index.html

Literature review

Belk (1995) refers to collecting as an activity that involves passion although it can border on the obsessive. There are various reasons why people collect, varying from the thrill to complete a collection, to collect to be part of a group (for example owning classic cars to be invited to car clubs). However, a substantial proportion of collectors also hope for financial gains (Burton and Jacobsen, 1999). The distinction between the demand driven by the intrinsic pleasures of ownership and the demand as an alternative financial asset was made by Satchell and Auld (2009) for stamps. Alternative investments refer to asset classes like stamps that fall outside the scope of many traditional investments such as stocks and bonds (Baker and Fillbeck, 2013).

The distinction identified by Satchell and Auld can have huge consequences for the market. Jens Berner, vintage car expert at Südwestbank AG said, "After the financial crisis, requests for alternative investments such as art, wine or classic cars had risen sharply.[8]

This sharp increase in demand for classic cars was noticed by Porsche. Porsche says in an article in the Porsche Klassik magazine that investors who are buying cars for profit rather than to drive are "spoiling the market" by "causing an explosion in prices even for 'normal' Porsche vehicles". What bothers them most, is that "this demand has sent prices skyrocketing and left an increasing number of old Porsche vehicles sequestered in garages, rarely or never seeing the light of day because they were bought purely as investments".[9]

The costs involved with investing in cars

Transaction costs

Transaction costs are an important cost associated with investments in classic cars. Auction houses are known for charging premiums on auction prices for the buyer of a lot, and charging commissions on a sold lot to the seller. These costs "can easily amount to more than 25% of the asset its price" (Dimson & Spaenjers, 2014). However, since holding periods for classic cars tend to be long, the impact of transaction costs on net annualized returns is decreasing in the long-term.

Another part of the transaction cost that is important to identify are illiquidity costs. Unlike equities, collectible assets cannot be sold at any time for the market price. Considering auction houses, it takes time to value each lot, creating the catalogues and market the auctions. Furthermore, there are only a limited number of auctions each year, all having their own target market. For example, Bonhams hosted an Aston Martin sale in May 2019.[10] Enthusiasts of Aston Martins are all aware of this auction, resulting in higher prices for the cars. If one wants to sell an Aston Martin two months after this auction, it might result in a sale far below market value. Therefore, timing of sale is very important and illiquidity costs can be substantial.

Other costs

There are several other costs investors have to take into account. Classic cars are delicate objects. Therefore, the cars need to be stored in climate controlled garages. Also, to keep the cars in the best condition as possible, regular maintenance is needed. Unfortunately, the service station around the corner probably cannot fix a classic car. The older the car, the harder it is to find replacement parts and qualified mechanics, resulting in higher costs.[11] Lastly, one needs insurance on the cars. Depending on the rarity of parts and the price and uniqueness of the car, insurance costs can be sizable.

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[8] https://www.bloomberg.com/news/articles/2018-07-09/vintage-porsches-683-gain-fuels-returns-in-carmakers-homeland

[9] https://www.autocar.co.uk/car-news/industry/porsche-article-car-investment-buyers-are-immoral

[10] https://www.bonhams.com/auctions/25452/#/!

[11] https://www.capitalgroup.com/pcs/latest-perspectives/Pleasures-and-Perils-of-Investing-in-Classic-Cars.html

The risks involved with investing in cars

Besides market risk, there are several other risk factors an investor needs to think about. First of all, damages to the car can be disastrous for the value of a car. If a car is completely original, with its first layer of paint still on it, a scratch on the paint could mean the value would plummet. Secondly, since the price of classic cars is rising, they become more interesting for thieves.[12] Risk of losing the vehicle due to a robbery is therefore increasing as well. Lastly, there is the event of fraud. Sellers could manipulate several features of the car to make it more interesting and get a higher price for the car. Examples can be turning back the odometer, omitting repairs on the maintenance report etcetera.

Alternative investments

Investment performance

The performance of alternative investments, such as gems, stamps, art and wine has been widely studied. Graeser (1993) claimed that collectibles are generally a "poor long-term investment". Although Graeser also mentioned that fine wine forms a possible exception to this assessment.

However, was Graeser right in 1993? If one looks at the investment performance of art, there are several papers that studied this market. Dimson and Spaenjers (2014), Renneboog and Spaenjers (2013) and Worthington and Higgs (2004) found that the returns in the art market were similar to that of bonds, whereas the risks were much higher. Therefore, making the art market not an interesting alternative asset. Next to that, Renneboog and Van Houtte (2002) found that the return on the niche art market of Belgian artistic schools from the 1850s till the 1950s is also underperforming compared to stock market returns.

Dimson and Spaenjers (2011; 2014) investigated the returns of stamps. Their findings for stamps were comparable to that of art: as a financial investment, the stamps have outperformed bonds, but underperformed stocks, while they approach the same volatility levels as stocks.

The optimism formed by the claims of Graeser in 1993 that wine forms a possible exception was supported by James J. Fogarty (2010) and Dimson, Rousseau and Spaenjers (2015). Fogarty came to the same conclusion that the return and the risk adjusted excess return to Australian wine was lower than for the standard financial assets. Whereas Dimson, Rousseau and Spaenjers concluded that although wine was outperformed by equities, the performance of wine has been better than that of art and stamps. However, the claims were shut down by Burton and Jacobsen (2001). They concluded that wine, just like other collectibles, "is only questionably a profitable investment instrument. The recent average annual rate of return on wine, together with the risk inherent in such an investment, does not justify retaining it as an alternative to equity, and its volatility likely makes it less desirable than debt for the majority of investors."

Nonetheless, Renneboog and Spaenjers (2012) studied the return on investment grade gems. They found that the annual real returns for white and coloured diamonds are 10% and 5.5% respectively, and the real return for other gems is 6.8%. therefore, these three assets have been outperforming the stock market since 1999.

Diversification gains

Besides investment performance, the possible diversification gains alternative assets have on an already diversified portfolio has been studied. Worthington and Higgs (2004) and Renneboog and Van Houtte (2002) investigated the possible diversification gains for the art market. The low correlations between the returns of art works and the financial assets found by the same study, were suggesting that there might be a benefit. However, due to the inferior risk-return attributes of art works compared to other financial assets such as stocks and bonds, "inclusion of these assets for diversification purposes in financial asset portfolios cannot be supported''

[12] https://www.telegraph.co.uk/motoring/10225872/Classic-car-theft-on-the-rise.html

(Worthington & Higgs, 2004). Renneboog and Van Houtte (2002), found that the Markowitz efficient frontier consisting of both art investments and equity does not shift upwards. The inclusion of art results only in an extension of the efficient frontier for very high levels of risk, meaning that the diversification effects of art in such a portfolio is limited (Renneboog & Van Houtte, 2002).

However, the research done by Fogarty (2010) found that with a positive allocation to wine in a mean-variance portfolio, the total portfolio risk compared to a diversified portfolio without wine, decreased by approximately 6.7%, for the same level of return. Thus making wine a good addition to a diversified portfolio.

Investment performance of cars

Although alternative assets like art, stamps and wine have been widely studied over the past years, the fast-growing market that investments in cars is, as it grew by more than 200% between 2009 and 2016, has been neglected (Martin, 2016). Up to this moment, there only have been two studies (as I know of) that investigated the investment performance of cars. Furthermore, none of these papers look at the diversification gains cars might have on a diversified portfolio.

Martin (2016) found annual returns with Blue Chip cars and German cars averaging a holding period return of 322.97% and 285.39% between 2007 and 2016 respectively. The worst performing categories were 1950s American and Muscle Cars, with holding period returns of 12.4% and 12.5% respectively. These holding period returns correspond to annual returns of 18.10% and 18.22% for the Blue Chip and German Collectibles, and 2.32% and 3.23% for the 1950s American and Muscle cars respectively. The highest performing categories of Classic Cars outperformed other financial assets like equities and bonds. However, as found with other alternative assets, with high volatility levels of 0.2324 and 0.2278 for Blue Chip and German cars respectively. Although, it must be noted that this research was done with limited data, since a sample of 96 collectible automobile types was analysed from 2007 to 2016. To overcome this issue, I use a dataset consisting of more than 25.000 auction records, from 2002 up to 2019.

Recently, Laurs & Renneboog (2019) wrote a paper about the investment performance of cars. They constructed a hedonic regression index with auction data between 1998 and 2017, with over 29.000 cars included, production years varying from the Veteran cars (1888-1907), to the Modern classics (1975-1990). This index appreciated at a yearly average nominal rate of 5.63% and thereby outperforming other asset classes, both in absolute terms as on a risk-adjusted basis (Sharpe ratio). As seen before with other alternative assets, the volatility of classic cars was lower than that of equities, but larger than that of government bond returns. Although they look at correlation between cars and other financial assets, they are not investigating the diversification benefits of adding cars to a diversified portfolio. They found negative correlations between cars and inflation, S&P500, MSCI World index, Government Bonds, Gold, Art and Bills. This implies that cars could have a beneficial impact on portfolios. However, it requires additional research to calculate the impact it has on these portfolios.

In this paper, both the investment performance of cars as the portfolio diversification gains are studied based on a large dataset (more than 25.000 auction records over the last 17 years). Furthermore, instead of using the common Sharpe ratio as a risk-adjusted performance measure, another measure, the RAP as proposed by Modigliani and Modigliani (1997), is used to make the outcome more understandable and easier to interpret for non-professional investors.

Data collection

To obtain auction results, I use the online Sports Cars Market Database. This database is the most comprehensive database for car auctions. It contains more than 351.000 records in total. The database splits the information over the lots sold up in different sections.

First of all, there is the header ‘Basic Information’. Under this header some general information on the car is stated. This includes the car details, like the year it was built and the make and model of the car, information on the sale details and information on the auction.

Next, there is the header ‘Condition Description’. This part gives some background information on the car, like the car its condition and history of the car. It is written by an expert who is affiliated to Sports Cars Market.

Thirdly is ‘Market Opinion’. It gives some information about earlier sells (if applicable) and what the car was supposed to be worth approximately. This information is often missing and therefore not useful to include in the database. However, for racers it is there all the time and I use it to find background information on racers.

After that, there is a header called ‘Vehicle Information’. In this part the more specific details of the car are disclosed. Chassis/VIN number, engine type, transmission, displacement, induction, condition and body style are all mentioned and included in the database. Also the features of the car are mentioned in this part, the features included are wheels, seats, exterior and interior. The condition of the car can vary from 1 to 6, where 1 is ‘National concours standard/perfect’ and 6 is ‘Good only for parts’. Since condition 6 cars are sold just for their parts and not as a running car, I exclude them from my dataset.

Seeing that information is missing from records without pictures, I exclude those as well from the dataset. The unsold vehicles, lots that come up for sale at the auction but do not sell, are removed too, as they are not representing the true value of the car at that time since no one was willing to pay the asking price. Due to the fact that my analysis is based on cars from 1947 until 2019, I exclude all the records that are not in this timeframe. I remove all the records with an auction value lower than 1.000 USD. I also delete the unpublished results, the ones that are sold by private treaty and everything that is not a car, such as motorcycles and boats. After that, I do a check to make sure there are no duplicates and delete all the duplicates found. Lastly, I delete the records that are not complete after I try to find the missing information manually.

To construct real auction prices, I need to correct the prices for inflation. To do so, I use a US Consumer Price Index. To construct my portfolios, I need some other financial assets. Data regarding a World Government Bond Index, a World Stock Index and the Three-Month US Treasury Bill are all collected from the Thomson Reuters Datastream.

Methodology

Cars are ''products whose characteristics vary in such a way that there are distinct product varieties even though the commodity is sold in one market'' (Taylor, 2017). Due to these variations in products, in this case cars, the product variations will lead to different prices. A car with a V8 might, for example, have a higher price than that same car with a V6. By using a hedonic pricing method, it is possible to construct a price index by taking into account the key characteristics of the cars used to construct the index. Or as Rosen (1974) put it: ''hedonic prices are defined as the implicit prices of attributes and are revealed to economic agents from observed prices of differentiated products and the specific amounts of characteristics associated with them''.

For this analysis, I use the time dummy variable method. This method is called the direct method, since ''the index number is estimated directly from the regression, without another intervening calculation''(Triplett, 2004). The direct time dummy variable method captures the time effects on the hedonic price index. A hedonic price index is any price index that makes use of a hedonic function, which is a relation between different varieties of in this case cars, and the quantities of characteristics in them, such as body type and displacement. The direct time dummy variable method regression (hedonic function) is as follows:

$$Log\ Price_{it} = \alpha + \sum_{m} \beta_m V_{mit} + \sum_{t} \gamma_t \delta_{it} + \varepsilon_{it}$$

Equation 1. The hedonic function used to create the hedonic price index.

Where $Log\ Price_{it}$ is the natural logarithm of the auction price corrected for inflation for car i at time t. V_{mit} is the variable that stands for all the dummy variables that are associated with vehicle information. The variable δ_{it} relates to the date of auction and takes the value of 1 if car i is sold in period t and 0 otherwise. The coefficients β_m reflect the attribution of a relative shadow price to each of the m characteristics. The time dummies of the model capture the time effects on the price index. A dummy variable takes the value of 1 if that characteristic belongs to that car and 0 otherwise.

To create a price index, the log prices must be converted back to normal prices. This can be done by using the exponents of the regression coefficients of the years.

$$I_t = \exp(\gamma_t) * 100$$

Equation 2. Using the exponents of the regression coefficients of the years to convert the log prices back to normal prices.

Where I_t is the car price index at time t, and γ_t is the time dummy coefficient of year t. The returns calculated from the index are geometric returns and therefore still need to be corrected for the logarithmic transformation bias (Laurs & Renneboog, 2019). This can be done by using the following formula:

$$I_t^* = I_t \exp(\frac{\mathrm{SE}_{\gamma_t}^2}{2})$$

Equation 3. Correcting the geometric returns for the logarithmic transformation bias.

Where I_t^* is the corrected index level at time t. I_t is the car price index at time t, and $SE_{\beta t}^2$ is the squared standard error of the dummy coefficient corresponding to year t. In addition to the regression tables, a relative price impact is calculated, as done by Laurs & Renneboog (2019). The relative price impact shows the performance of a characteristic compared to the reference characteristic for that category. Therefore, it becomes easier to compare the performance of, for example, different makes and body types. The formula is as follows:

$$\frac{\delta P_i}{P_i} * 100\% = (\exp(\beta_m) - 1) * 100\%$$

Equation 4. The relative price impact.

The first part of the formula, $\frac{\delta P_i}{P_i}$ is the marginal price impact and β_m is the coefficient of characteristic m.

To make the hedonic regression as explanatory as possible, it is necessary to include as many compelling characteristics corresponding to the car as possible. This is due to the fact that the hedonic characteristics capture a large proportion of the variance in the dependent variable. Therefore, the more credible characteristics included in the regression, the more variance in the dependent variable LogPrice is captured and the model will thus be more accurate.

The first characteristic is the condition of the car. The condition of the car can vary from 1 to 6, where 1 is 'National concours standard/perfect' and 6 is 'Good only for parts'. As mentioned earlier, I exclude all the cars with condition 6.

Condition	Observations
C1	4128
C2	10753
C3	8457
C4	1449
C5	306

Table 1. The dummy variable 'Condition', varying from C5 to C1, where C5 is 'a nasty beast that runs but has many problems' and C1 is 'National concours standard/perfect' and the corresponding number of observations in the dataset.

Next, all the auction houses with more than 50 records in the database are added. The other auction houses are grouped and can be found under 'Other auctions houses'.

Auction House	Observations
Classic Motorcar Auctions	62
Brightwells	67
The Finest	70
Potts Auction Company	72
Twin Cities Auctions	75
Hollywood Wheels	81
Vicari	82
Shannons	85
Coys	93
MidAmerica	96
Lucky Collector Car Auctions	101
Collector Car Productions	102
Motostalgia	132
Dan Kruse Classics	166
VanDerBrink Auctions	234
GAA	236

Christie's	242
Carlisle Events	247
Kruse	439
eBay	467
Leake	527
The Branson Auction	584
Silverstone	680
RM Sotheby's	687
H&H Auctioneers	698
Artcurial	713
McCormick's	724
Other auction houses	740
Russo and Steele	841
Auctions America	841
Worldwide Auctioneers	873
Gooding & Co.	912
Silver Auctions	1044
Barrett-Jackson	2643
Mecum Auctions	2747
RM Auctions	2807
Bonhams	3883

Table 2. Auction houses with more than 50 observations. The other auction houses are grouped and can be found under 'Other auction houses'.

The engine of the car, ranging from a one cylinder to a W16 are also specified. I create a dummy variable that equals 1 if the car has that type engine and 0 otherwise.

Engine	**Observations**
1-cylinder	121
H12	122
H2	54
H4	708
H6	812
H8	1
I2	137
I3	17
I4	3051
I5	32
I6	4201
I8	251
Rotary	23
V2	9

V4	62
V6	692
V8	13198
V10	89
V12	1491
V16	13
W12	4
W16	5

Table 3. The engine of the car and the corresponding number of observations.

Another variable that is controlled for is the transmission using dummy variables, with three possible options: A manual -, automatic - and semiautomatic transmission. The dummy variable takes the value of 1 if a car its transmission belongs in that category and 0 otherwise.

Transmission	**Observations**
Manual	16075
Automatic	8984
Semi-automatic	34

Table 4. The transmission of the car and the corresponding number of observations.

The displacement of the car in cubic centimetres is grouped in the following categories: [40;1150], [1150;2050], [2050;3050], [3050;4050], [4050;5550], [5550;7050], [7050, 39000]. The dummy variable takes the value of 1 if a car its displacement belongs in that category and 0 otherwise.

Displacement in cc	**Observations**
40:1150	835
1150:2050	3138
2050:3050	3414
3050:4050	3274
4050:5550	6551
5550:7050	6808
7050:39000	1073

Table 5. The displacement of the car in cubic centimetres and the corresponding number of observations.

Induction is a dummy variable that takes the value of 1 if a car has any form of forced induction, and 0 otherwise. There are 22596 cars with any form of forced induction in my database.

The odometer is grouped as well. The categories are as follows: [0;15000], [15000;30000], [30000;50000], [50000;75000], [75000;100000], [100000;∞]. The dummy variable takes the value of 1 if a car its odometer belongs in that category and 0 otherwise.

Odometer	Observations
0:15000	5144
15000:30000	3204
30000:50000	4100
50000:75000	4840
75000:100000	3568
100000:∞	4231

Table 6. The odometer of the car and the corresponding number of observations.

Body types are controlled as well. Varying from buggies to racers. The dummy variable takes the value of 1 if a car its body type corresponds to the specified category and 0 otherwise.

Body Type	Observations
Buggy	6
Convertible	7362
Coupe	9880
Fastback	671
Hatchback	162
Limousine	124
Microcar	66
Pickup	624
Racer	528
Roadster	2355
Sedan	2010
SUV	232
Targa	183
Tourer	9
Utility	234
Van	160
Wagon	487

Table 7. The body type of the car and the corresponding number of observations.

Colours are controlled for also. Unclear colours, like cay coral, are hand checked to make sure all colours are present in the right category. If the colour corresponds to the specified category, the dummy variable takes the value of 1 and 0 otherwise.

Exterior	Observations
Beige	208
Black	2793
Blue	3841
Bronze	141
Brown	213
Charcoal	16

Copper	69
Cream	288
Gold	466
Green	2206
Grey	711
Ivory	158
Maroon	548
Orange	601
Pink	182
Primer	10
Purple	197
red	5925
Rust	5
Silver	1881
Tan	146
Turquoise	235
White	2971
Yellow	1282

Table 8. The exterior colour of the car and the corresponding number of observations.

All makes that appear at least ten times in the database are included, the other makes are grouped and are called 'Other makes'. This is a dummy variable too, that takes the value of 1 if the car is the specified make and 0 otherwise. In the table below, all makes with more than or equal to one hundred observations are included. The complete table can be found in the appendix.

Make	**Observations**
Land Rover	100
Austin	101
Toyota	106
Studebaker	122
Citroën	122
AMC	124
Packard	138
Lotus	139
Triumph	186
Lamborghini	208
Lancia	216
Mercury	239
Fiat	264
Lincoln	286
Bentley	293
Maserati	299

Chrysler	304
Rolls-Royce	305
BMW	340
Austin-Healey	351
Oldsmobile	382
Volkswagen	404
MG	417
Alfa Romeo	446
Buick	468
Dodge	494
Cadillac	502
Plymouth	522
Shelby	529
Other makes	747
Pontiac	765
Aston Martin	789
Jaguar	1178
Mercedes-Benz	1188
Porsche	1222
Ferrari	1682
Ford	2131
Chevrolet	4794

Table 9. The make of the car and the corresponding number of observations. Makes with less than 10 observations are grouped and can be found under 'Other makes'.

To control for production year, I include categories. Cars build between 1947 and 1975 are post-war classics, however, due to the size of this group, I split this group in two separate groups, one from 1947 till 1965 and one from 1965 till 1975. Then I have the group Modern Classics, ranging from 1975 till 1990. The cars from 1990 till 2003 are called the Youngtimers and cars less than 15 years old are not classified as classic cars and are therefore called 'New'.

Category	**Observations**
1947-1965	10387
1965-1975	9321
1975-1990	3138
1990-2004	1617
2004-2019	630

Table 10. The era when the car was built and the corresponding number of observations.

To check for prestigious auctions, I include the variable for the three most prestigious auctions namely Goodwood Festival of Speed, Goodwood Revival and Pebble Beach concours d'Elegance. If a car was sold at one of these events, the variable will take the value 1 and 0 otherwise.

Prestigious Auctions	Observations
Goodwood Festival of Speed	306
Goodwood Revival	250
Pebble Beach Concours d'Elegance	592

Table 11. The prestigious auctions and the corresponding number of observations.

Besides that, I run a different regression for the racers. I added dummy variables to quantify the history of these cars. First of all, the variable Provenance is added. This variable is 1 if the car appeared at Daytona, Sebring, Le mans, F1, Indycar, NASCAR or the 24 hour race of Spa Franchorchamps. If not, this variable takes the value 0. There are variables for performance as well. These variables are:

'Winner', 1 if the car won one or multiple races and 0 otherwise. 'Podium' is 1 if the car was on the podium but did not win, and 0 otherwise. 'Retired' is 1 if the car participated in a race but did not finish it. 'Fatal Accident' is 1 if the car was involved in a deadly crash and 0 otherwise. Then there is a variable 'Replica'. This variable will be 1 if the car is a replica of a racer. Lastly there is a variable 'FamousOwnerDriver' that will take the value of 1 if the car was driven or owned by a celebrity. A celebrity is identified as a celebrity if the previous owner is, or the previous owners are, mentioned by name in the description given in the database.

History	Observations
Provenance	120
Winner	91
Podium	12
Retired	7
Fatal accident	2
Replica	421
Famous owner/driver	223

Table 12. The history of racers and the corresponding number of observations.

Investors might have preference for cars from a specific country, like Italian or British. To see how the makes from specific countries perform, I run different regressions and create an index as well. This is also done for production year categories, as aforementioned. Next to that, I run a regression with the convertibles and roadsters combined and see how they perform.

Additionally, it is interesting to see how an investor would have performed if one decided upon a strategy in 2010. To do so, I run a regression with all the data available up to 2009. From then on, I pick the characteristics with the highest positive coefficients, as they have the largest impact on the (log) price. Consequently, I run a regression with data from 2010 onwards only including cars which have at least one of the five picked characteristics and create an index afterwards.

After the index is created, efficient portfolios are constructed based on the expected return-risk model. One of the founders of the Modern Portfolio Theory (MPT) is Harry Markowitz. He wrote a paper in 1952 about portfolio selection and is seen as the foundation for the MPT. Markowitz was the first to recognize the importance of the combined effects of return, risk and covariances, when creating portfolios. For example, Markowitz claimed that investors who want to minimize variance it is not enough to just invest in many securities. They '' should diversify across industries because firms in different industries, especially industries with different economic characteristics, have lower covariances than firms within an industry'' and therefore will have lower variances and thus lower risk (Markowitz, 1952).

I use a traditional expected return-risk efficiency model to determine the weights allocated to each asset that define portfolios on the risk-efficient frontier. An investor can choose any efficient portfolio on this frontier depending on the risk they are willing to bear. The efficient frontier describes the set of portfolios that minimize the risk for a specified rate of return. To come to the efficient frontier, one has to allocate weights to the assets so that the variance of the portfolio is minimized and that the portfolio equals a specified return. By repeating this process for multiple returns, an efficient frontier can be constructed. To do so, the return, variance and the covariance of all the assets are required.

To make it more visible, let me explain it by showing the mathematics by giving an example of two risky assets. R_1 and R_2 are the returns on the two assets. ''a'' is the fraction of wealth invested in asset 1 and $1 - a$ is the fraction of wealth invested in asset 2. $E(R_1)$ and $E(R_2)$ are the expected values and $V(R_1)$ and $V(R_2)$ are the respective variances. As mentioned earlier, one has to choose an optimal a to minimize the portfolio variance, taking into account a specified return $E(R_p) = m$, where m is the target return. The expected return and variance for the portfolio can be defined as:

$$E(R_p) = a * E(R_1) + (1 - a) * E(R_2) = m$$

Equation 5. The expected return for portfolio p.

and

$$var(R_p) = a^2 * var(R_1)^2 + (1 - a)^2 * var(R_2) + 2 * a * (1 - a) * cov(R_1, R_2)$$

Equation 6. The variance for portfolio p.

If one has many risky assets, the problem can be solved using matrix notation. Where ω is a vector of weights assigned to each asset, and ∑ is the variance-covariance matrix of the portfolio (Bodie, Kane, & Marcus, 2014). This results in the following notation:

$$Min\{var(R_p) = \omega' \sum \omega\}$$

Equation 7. Solving the optimization problem for many risky assets using matrix notation.

With the constraint

$$st. \omega' * E(r_p) = m$$

Equation 8. the constraint that the weights multiplied by the expected return of the portfolio equals the target return m.

To construct the portfolios, I minimize the variance by changing the weight allocation of the assets. Furthermore, as discussed earlier, a target return is specified. By defining multiple target returns, the efficient frontier is constructed. I do this for the index with all the cars, the index constructed by eras, the one by make, the one by body type (convertibles, roadsters and racers) and I create one portfolio without cars. This portfolio consists of the MSCI World Stock index, which is a broad global equity index that represents large and mid-cap equity performance across 23 developed markets countries. Next to that, I use the FTSE World Government Bond Index (WGBI). The WGBI measures the performance of fixed-rate, local currency, investment-grade sovereign bonds. Lastly, to complete the portfolio consisting of financial assets only, I add the risk-free rate. The risk-free rate I use is the Three-Month Treasury Bill.

After the portfolios are constructed, they need to be compared with a measure that takes both risk and return of the portfolio into account. The most used way of doing so is by using the Sharpe ratio. This method was proposed by William Sharpe in 1966. He called it the reward-to-volatility ratio. It is defined as the ratio of the difference between return of the portfolio and return of the risk-free asset to the volatility (standard deviation) of the portfolio's return. This results in a measure of ''reward per unit risk'' (Sharpe, 1966). However, the outcome of this ratio is hard to interpret for normal investors.

Franco – and Leah Modigliani proposed another Risk Adjusted Performance (RAP) measure. This measure ''adjusts all portfolios to the level of risk in the unmanaged market benchmark, example given the S&P 500, thereby matching a portfolio's risk to that of the market, and then measuring the returns of this risk-matched portfolio'' (Modigliani & Modigliani, 1997). In other words, it adjusts every portfolio to the same level of risk as the benchmark; the market portfolio consisting of financial assets only. Since all portfolios are now on the same scale, it becomes clear to see the difference in performance of various portfolios for the same level of risk, as illustrated by Modigliani & Modigliani in figure 1 (1997). The portfolio with the highest RAP performs best and vice versa.

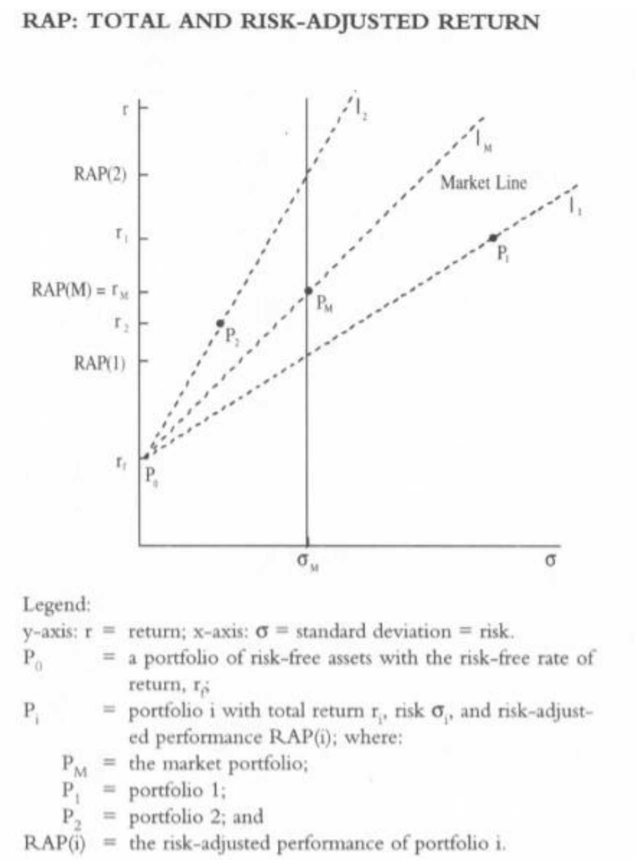

Figure 1. Graphical representation of the RAP taken from Modigliani and Modigliani (1997). It is shown that for the same level of risk, different returns are realized. Since they have the same level of risk, the different returns can be compared

The outcome of this measure is equal to the outcome of the Sharpe ratio, meaning that the same portfolios are identified as the best and the other way around. However, the main benefit of this measure compared to the Sharpe ratio is that the RAP is expressed in basis points and therefore easy to understand, whereas the Sharpe ratio can be challenging to interpret for non-professional investors. Furthermore, it makes it easier to compare different portfolios than for example with the Sharpe ratio, since the difference between the portfolios is expressed in basis points as well. To calculate the RAP, I use the following formula:

$$RAP = \left({}^{\sigma_M}/_{\sigma_i}\right)\left(r_i - r_f\right) + r_f$$

Equation 9. The Risk-Adjusted Performance measure proposed by Modigliani & Modigliani.

Where σ_M is the standard deviation of the market portfolio, the portfolio consisting of the thee-month T-bills, the world government bonds and the MSCI World Stock returns. σ_i is the standard deviation of portfolio i, consisting of the financial assets aforementioned, and cars. The return r_i is the average return on portfolio i, and r_f is the average risk free rate of the sample period.

To identify the corresponding standard deviations and returns, I maximize the Sharpe Ratio for all the portfolios. By maximizing the Sharpe Ratio, the optimal risk-return trade off can be found.

Results

After running the hedonic regression models described previously, table 1 is constructed. It captures all the aforementioned characteristics included in the hedonic regression model. The dependent variable is the LogPrice, and the other independent variables are included as dummy variables. For the whole sample, the independent variables explain 69.1% of the price variation. Firstly, I discuss some statistically significant characteristics and their relative price impact. By looking at the coefficients for the condition characteristics, one can see that cars in better conditions (1 and 2), sell for higher prices than cars in worse conditions (3 and 4). Cars in perfect condition, condition 1, sell on average for more than 133% than the price of the reference condition, condition 3. Furthermore, cars sold at Gooding & Company, the auction house that also hosts the prestigious Pebble Beach Concours d'Elegance, outperforms Silver Auctions by a stunning 322.91%. Next to that, racers and roadsters are the best performing body styles according to the sale price with higher prices than that of sedans of 342.38% and 132.80% respectively. Aston Martins go for a much higher price than Chevrolets, with an impressive 392.83% price premium. However, McLarens have a higher price on average than Chevrolets of an astonishing 2228.94%. As expected, all three prestigious auction events, Goodwood Fesitval of Speed, Goodwood Revival and Pebble Beach show positive coefficients, meaning that the average price of cars sold is higher at these auctions.

Table 13. This table shows the regression results for the whole sample regression. The reference category by type of variable is indicated with a # next to the variable. ***, ** and * stand for statistical significance on a 1%, 5% and 10% level respectively. Next to the coefficients, the relative price impact is shown in percentages.

WholeSample	Coefficient	Relative PI
Condition 1	0.849***	133.73%
Condition 2	0.442***	55.58%
Condition 3#	N/A	
Condition 4	-0.411***	-33.70%
Condition 5	-0.713***	-50.98%
SilverAuctions#	N/A	
RMSothebys	1.608***	399.28%
HHAuctioneers	0.503***	65.37%
Artcurial	1.182***	226.09%
McCormicks	0.212***	23.61%
AuctionsAmerica	0.499***	64.71%
GoodingCo	1.442***	322.91%
BarrettJackson	0.821***	127.28%
MecumAuctions	0.668***	95.03%
RMAuctions	1.116***	205.26%
Bonhams	0.925***	152.19%
OtherAuctions	0.245***	27.76%
Convertible	0.585***	79.50%
Coupe	0.504***	65.53%
Fastback	0.611***	84.23%
Hatchback	0.567***	76.30%
Limousine	0.459***	58.25%
Racer	1.487***	342.38%
Roadster	0.845***	132.80%
Sedan#	N/A	
McLaren	3.148***	2228.94%

Shelby	0.869***	138.45%
Pontiac	-0.082***	-7.87%
AstonMartin	1.595***	392.83%
Jaguar	0.498***	64.54%
MercedesBenz	0.505***	65.70%
Porsche	0.875***	139.89%
Ferrari	0.878***	140.61%
Ford	-0.099***	-9.43%
Chevrolet#	N/A	
OtherMakes	0.304***	35.53%
Postwar	0.301***	35.12%
Y1965Y1974	-0.027	-2.66%
Modern	-0.665***	-48.57%
Youngtimer	-0.602***	-45.23%
New#	N/A	
American	0.021	2.12%
British	-0.337***	-28.61%
Italian	0.414***	51.29%
German	0.062	6.40%
French	0.309**	36.21%
Japanese	0.081	8.44%
GoodwoodFestivalofSpeed	0.121*	12.86%
GoodwoodRevival	0.218***	24.36%
PebbleBeach	0.269***	30.87%
Constant	8.862***	
Observations	25,093	
R-squared	0.691	
Year Fixed Effects	YES	

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The index constructed using the regression coefficients can be found in table 14. The average arithmetic return is 1.46%, with a standard deviation of 10.08%. However, since it is very unlikely that an investor would invest in such a general set, more specific sets are made in an identical way.

Year	**Coefficient**	**Index**	**Return**
Y2002	0	100	
Y2003	0.1013383	113.044868	13.04%
Y2004	-0.1163295	90.0216806	-20.37%
Y2005	0.0254307	103.719736	15.22%
Y2006	0.0857464	110.166415	6.22%
Y2007	0.0939985	111.082592	0.83%
Y2008	0.1308934	115.259326	3.76%
Y2009	0.0803556	109.586798	-4.92%
Y2010	0.0582747	107.193716	-2.18%

Y2011	0.070121	108.468387	1.19%
Y2012	0.0335328	104.568285	-3.60%
Y2013	0.2159181	125.493316	20.01%
Y2014	0.3210452	139.402453	11.08%
Y2015	0.379481	147.802364	6.03%
Y2016	0.2938312	135.672245	-8.21%
Y2017	0.309682	137.829062	1.59%
Y2018	0.2116803	124.96384	-9.33%
Y2019	0.1542647	118.057117	-5.53%
Average return			1.46%
standard deviation			10.08%

Table 14. The index constructed using the regression coefficients. The average return for the whole sample is 1.46% with a risk level of 10.08%.

I create indices regarding eras, country of make, certain body types and the out-of-sample strategy. The eras I used are Postwar (1947-1964), Y1965-Y1974, Modern Classics (1975-1989), Youngtimers (1990-2003) and New (2004-2019). As one can see in table 15, the average returns regarding the identified eras vary from -0.73% for cars build between 1975 and 1989, up to 4.59% for cars build in the last fifteen years. The standard deviation, thus the risk, varies a lot. Where it is 10.67% for the period 1947-1964, it is 46.88% for the 'Youngtimers'.

Average returns	**1947-1964**	**1965-1974**	**1975-1989**	**1990-2003**	**2004-2019**
Y2002	0.00%	0.00%	0.00%	0.00%	0.00%
Y2003	-2.14%	34.33%	-46.01%	170.08%	0.00%
Y2004	-5.63%	-16.88%	-26.36%	-71.37%	0.00%
Y2005	13.38%	22.52%	0.85%	-13.79%	30.77%
Y2006	18.49%	4.07%	7.12%	-27.81%	-13.90%
Y2007	-3.03%	0.80%	6.79%	6.59%	27.82%
Y2008	6.71%	4.22%	-6.24%	-14.16%	-42.06%
Y2009	-4.41%	-6.94%	0.09%	2.20%	25.57%
Y2010	-4.35%	5.01%	3.33%	-8.71%	-21.17%
Y2011	8.39%	-5.27%	-5.74%	-3.19%	1.74%
Y2012	-10.18%	1.86%	4.91%	-4.83%	12.34%
Y2013	26.68%	15.94%	6.47%	3.93%	-3.45%
Y2014	0.55%	18.51%	24.95%	44.22%	7.05%
Y2015	13.14%	-0.93%	26.03%	1.47%	-1.89%
Y2016	-12.92%	-8.12%	-9.40%	-2.26%	42.25%
Y2017	1.51%	-3.25%	1.77%	1.72%	-5.54%
Y2018	-6.25%	0.28%	-16.98%	-17.29%	-19.57%
Y2019	-8.56%	-8.12%	15.28%	5.84%	42.70%
Average return	1.74%	3.22%	-0.73%	4.03%	4.59%
Standard deviation	10.67%	12.52%	17.08%	46.88%	22.55%

Table 15. The index constructed using the regression coefficients for the eras. The average returns regarding the identified eras vary from -0.73% for cars build between 1975 and 1989, up to 4.59% for cars build in the last fifteen years. The standard deviation, thus the risk, varies a lot. Where it is 10.67% for the period 1947-1964, it is 46.88% for the cars built between 1990-2003.

A country of make is included if at least 1% of the cars in the dataset are from that country. By doing so, the cars from the United States of America, Great Britain, Italy, Germany, France and Japan are included. By looking at table 16, one can see higher returns for Italian and Japanese cars, 12.48% and 5.94% respectively, than for the eras category. However, the same holds for their standard deviations, as they are 46.43% and 34.28% respectively.

Average returns	**American**	**British**	**Italian**	**German**	**French**	**Japanese**
Y2002	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Y2003	22.62%	0.00%	173.64%	-17.49%	0.00%	0.00%
Y2004	-16.45%	20.49%	-64.88%	-5.97%	-32.31%	-15.82%
Y2005	18.66%	1.85%	30.78%	-3.02%	-16.75%	-39.87%
Y2006	6.43%	18.62%	4.29%	12.96%	50.55%	66.30%
Y2007	-6.41%	13.08%	13.72%	14.31%	-16.44%	33.20%
Y2008	1.88%	0.00%	7.14%	8.65%	54.37%	-14.14%
Y2009	-6.55%	-16.95%	-7.11%	-0.37%	-13.47%	-14.68%
Y2010	-1.43%	4.43%	24.21%	-5.71%	5.83%	61.40%
Y2011	-4.34%	14.40%	-5.19%	19.12%	-10.97%	-40.77%
Y2012	-5.56%	-0.57%	-3.15%	-2.25%	42.52%	0.24%
Y2013	11.83%	25.32%	46.81%	21.55%	-23.77%	64.92%
Y2014	1.69%	4.16%	24.18%	14.75%	50.99%	-3.98%
Y2015	4.82%	19.45%	2.65%	9.37%	15.34%	-0.27%
Y2016	-7.25%	-4.94%	-8.53%	-3.86%	-9.12%	-19.79%
Y2017	0.25%	5.75%	4.06%	-9.37%	-2.93%	18.85%
Y2018	-2.04%	-15.29%	-18.45%	-1.76%	-0.07%	-28.83%
Y2019	-1.98%	-7.16%	0.44%	-7.12%	-17.96%	40.18%
Average return	0.90%	4.59%	12.48%	2.43%	4.21%	5.94%
Standard deviation	9.46%	12.02%	46.43%	10.90%	27.38%	34.28%

Table 16. The index constructed using the regression coefficients for the country of make. The returns for Italian and Japanese cars, 12.48% and 5.94% respectively, are higher than for the eras category. However, the same holds for their standard deviations, as they are 46.43% and 34.28% respectively.

The last category I look at are body types. I look specifically at convertibles, roadsters and racers. If one looks at table 17, one can conclude that roadsters are a better investment compared to convertibles. They achieve a higher return, 3.54% compared to 1.31% respectively, and a lower standard deviation, 9.96% compared to 12.81%. Racers have the highest return, 5.02%, although they also experience the highest risk, having a standard deviation of 30.05%.

Average return	**Convertibles**	**Roadsters**	**Racers**
Y2002	0.00%	0.00%	0.00%
Y2003	32.28%	0.00%	0.00%
Y2004	-25.11%	-1.20%	-51.65%
Y2005	17.03%	14.88%	-3.47%
Y2006	4.63%	20.50%	28.67%

Y2007	-0.71%	3.41%	8.78%
Y2008	2.48%	-0.97%	0.84%
Y2009	-12.27%	8.79%	-23.80%
Y2010	3.72%	-12.30%	67.26%
Y2011	-1.46%	3.94%	-24.00%
Y2012	-5.66%	1.53%	69.52%
Y2013	16.85%	23.01%	-7.04%
Y2014	7.46%	15.97%	5.54%
Y2015	2.30%	0.52%	20.97%
Y2016	-9.52%	-5.94%	8.62%
Y2017	5.95%	-1.08%	-29.75%
Y2018	-12.07%	-12.68%	1.01%
Y2019	-3.58%	1.75%	13.90%
Average return	1.31%	3.54%	5.02%
Standard deviation	12.81%	9.96%	30.05%

Table 17. The index constructed using the regression coefficients for the three identified body types. One can conclude that roadsters are a better investment compared to convertibles. They achieve a higher return, 3.54% compared to 1.31% respectively, and a lower standard deviation, 9.96% compared to 12.81%. Racers have the highest return, 5.02%, although they also experience the highest risk, having a standard deviation of 30.05%.

Lastly, I perform an out-of-sample analysis. This analysis represents the strategy an investor would have chosen if one wanted to invest in cars in 2010, using all the available data to the investor at that time. This analysis is done by running a regression with data up to and including 2009. After that, I look for the characteristics with the highest relative price impact, as they are outperforming the other characteristics and thus have the highest positive impact on the final sale price. The characteristics included are racer, copper, microcar, roadster and orange, as their relative price impacts are 711.31%, 411.22%, 374.94%, 373% and 364.41% respectively. A car is included in the dataset if it has at least one of the characteristics mentioned. By running a regression with the remaining dataset for the years 2010-2019, the returns in table 18 are found. One can see that this strategy, based on information that was available when the strategy was chosen, would have had a return of 5.56%, with a standard deviation of 21.31%.

Average returns	Out-of-Sample Analysis
Y2010	17.01%
Y2011	2.68%
Y2012	8.46%
Y2013	32.50%
Y2014	42.51%
Y2015	-1.11%
Y2016	-15.73%
Y2017	12.66%
Y2018	-29.87%
Y2019	-2.03%
Average return	5.56%
Standard deviation	21.31%

Table 18. The index constructed using the regression coefficients for the Out-of-Sample analysis. This strategy based on the characteristics racer, copper, microcar, roadster and orange has an average return of 5.56% and a standard deviation of 21.31%.

To calculate the diversification benefits of adding cars as risky assets to a financial asset only portfolio, I construct several portfolios using the theory firstly introduced by Markowitz in 1952 (Markowitz, 1952). Firstly, I construct a portfolio with the financial assets only.

This portfolio functions as the benchmark for the other portfolios. Furthermore, I create portfolios with all the cars, based on eras, based on makes, based on body types, based on optimal assets, all the risky assets (the eras, makes and body types) and the out-of-sample analysis.

The optimal assets can be chosen by looking at figure 2. By looking at figure 2, I chose roadsters, British cars and Italian cars as optimal assets.

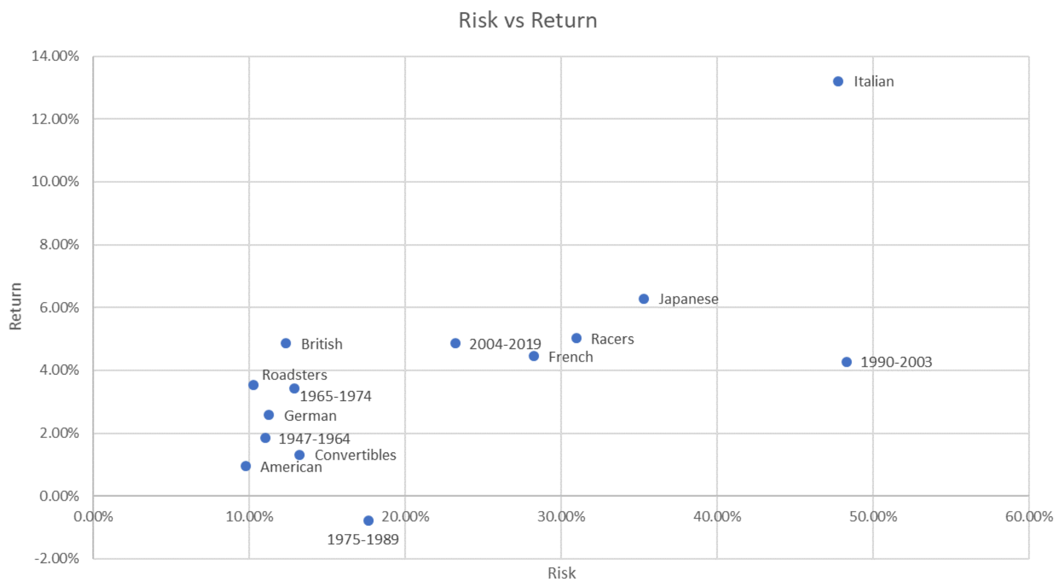

Figure 2. The risky assets are plotted based on their risk-return relationship.

Including these assets in a portfolio results in the following graph. It is no surprise that both the returns and the standard deviation are higher than in the portfolio with just the financial assets.

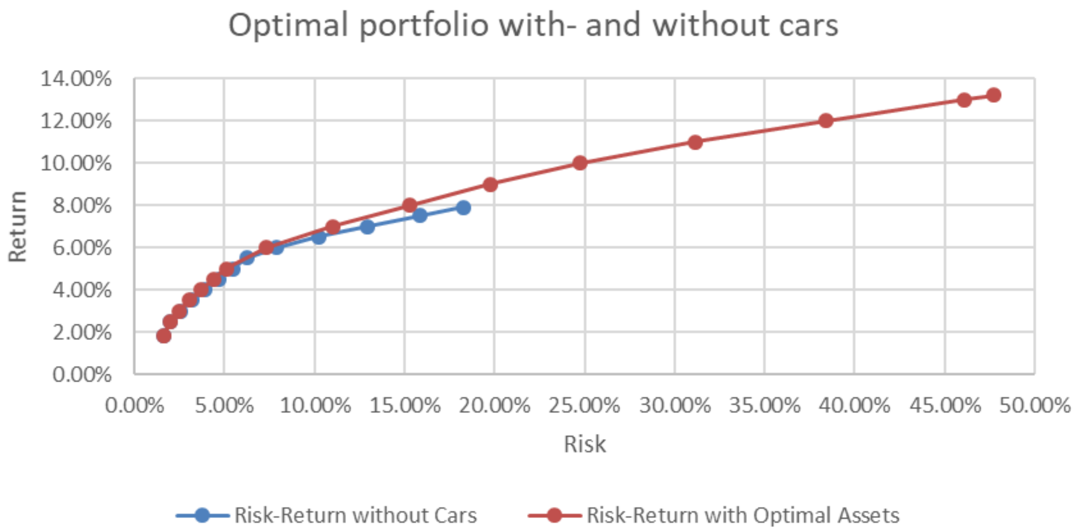

Figure 3. The performance of the portfolio without cars and the portfolio with the optimal assets (roadsters, British – and Italian cars) and the financial assets.

This graph as shown in figure 3 is constructed by controlling for specific returns with minimizing the standard deviation of the portfolio for the specified return. This results in the following weights:

Return	Risk	MSCI World Stock	Risk Free Rate	FTSE World Government Bond	British	Italian	Roadsters	Total
1.8%	**1.7%**	2.2%	95.5%	2.1%	0.0%	0.2%	0.0%	100.0%
2.5%	**2.0%**	5.8%	76.0%	15.5%	0.7%	0.0%	2.0%	100.0%
3.0%	**2.5%**	7.9%	60.9%	24.8%	2.0%	0.0%	4.3%	100.0%
12.0%	**40.8%**	0.0%	0.0%	0.0%	14.5%	85.5%	0.0%	100.0%
13.0%	**46.5%**	0.0%	0.0%	0.0%	2.5%	97.5%	0.0%	100.0%
13.2%	**47.8%**	0.0%	0.0%	0.0%	0.0%	100.0%	0.0%	100.0%

Table 19. The weights allocated to each asset for a target return while minimizing the standard deviation of the portfolio.

As one can see in table 19, the allocation for lower returns and risk is mostly based on the financial assets (MSCI World Stock, Risk free rate and the FTSE World Government Bond), whereas the allocation for the higher returns are in the risky assets only. For example, if one wants to have a return of 12%, one has a risk of 40.8% and invests 14.5% of their money into British cars and 85.5% of their investment into Italian cars.

All the portfolios are constructed in the same way. Their graphs and allocated weights can be found in the appendix.

To compare the portfolios, I use the Risk-Adjusted Performance measure as proposed by Modigliani and Modigliani (1997). The market portfolio is the portfolio consisting of financial assets only. By maximizing the Sharpe Ratio, the optimal risk-return trade-off is found. These returns and standard deviations are used in the calculations. The results of these calculations can be found in table 20.

Risk-Adjusted Performance	Average Return	Standard Deviation	Max Sharpe	Risk-Adjusted Return (RAP)
Portfolio without cars	5.43%	6.12%	0.62	5.43%
Portfolio General	5.22%	5.78%	0.63	5.44%
Portfolio Eras	4.35%	3.95%	0.69	5.85%
Portfolio Makes	4.88%	4.40%	0.74	6.15%
Portfolio Body Types	4.93%	4.70%	0.71	5.93%
Portfolio Optimal Assets	5.07%	5.18%	0.67	5.69%
Portfolio All Risky Assets	4.62%	3.76%	0.80	6.50%
Portfolio Out-of-Sample	2.77%	2.46%	0.67	5.23%
Three-Month T-Bill	1.61%			

Table 20. The average return, standard deviation, Sharpe ratio and Risk-Adjusted Return (RAP) are shown for the various portfolios. The portfolio with makes and the portfolio with all the risky assets outperform the portfolio without cars by 0.73% and 1.08% respectively, for the same level of risk.

The risk-adjusted returns can be found in the last column. The portfolio with all the cars (general portfolio) has a 0.01% higher return than the portfolio without cars for the same level of risk. This implies that investing in cars in general has very minimal diversification benefits. The out-of-sample analysis underperforms compared to the market portfolio. It has a 0.20% lower return for the same level of risk. However, by looking at the other categories, one can see that there are positive benefits. The portfolio with makes and the portfolio with all the risky assets outperform the portfolio without cars by 0.73% and 1.08% respectively, for the same level of risk. Thus, by adding cars to a financial asset portfolio, it is possible to achieve higher returns for the same level of risk. However, it is recommended to specify this investment into certain categories, with the category consisting out of eras, makes and body types achieving the best return for the same level of risk.

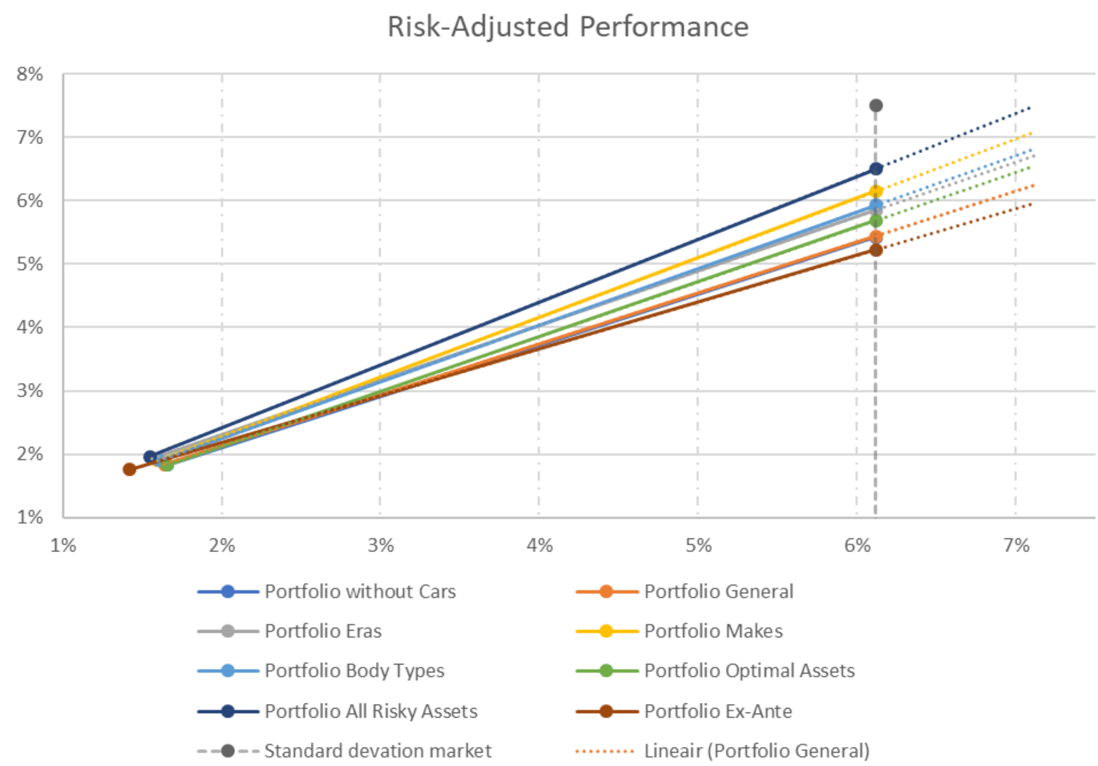

Figure 3. The Risk-Adjusted Performance of the various portfolios. The portfolio with all the risky assets is performing best, whereas the portfolio constructed using the Out-of-Sample analysis is performing worst.

Conclusion

Over the recent years, investments in alternative assets have become increasingly popular. A lot of research has been done on the risk and return and diversification benefits of art, stamps and wine. However, little research is done on the risk and return of cars and no research has been done regarding the potential for cars to provide a diversification gain to an already diversified portfolio.

To calculate the returns and risk involved with investing in (classic) cars, multiple hedonic regression indices are constructed based on an extensive dataset consisting of more than 25.000 auction results between 2002 and 2019. The independent variables explain 69.1% of the price variation for the whole dataset. It is found that if the condition of a car improves, the price goes up. The same holds for prestigious auctions, if a car is auctioned at Goodwood Festival of Speed, Goodwood Revival or Pebble Beach Concours d'Elegance, the average price of the cars auctioned is higher. Furthermore, racers and roadsters are the best performing body styles, with higher sale prices of 342.48% and 132.80% than sedans respectively. The return on cars for the whole dataset is 1.46%, which is lower than equities, bonds and even the risk-free rate. The standard deviation (risk) is 10.08%, which is lower than equities, yet higher than bonds. However, by focussing on eras, country of make or body types, higher returns can be realized. Cars that are less than fifteen years old have a return of 4.59%, Italian cars generate a return of 12.48% and racers have a return of 5.02%. Although it must be said that these higher returns go hand in hand with higher levels of risk, namely 22.55%, 46.43% and 30.05% respectively. Lastly, an out-of-sample analysis was performed. This analysis, based on the information available to the investor at the time of the hypothetical investment, would have had a return of 5.56%, with a standard deviation of 21.31%.

Thereafter, multiple investment portfolios are created. By using the Risk-Adjusted Performance (RAP) measure proposed by Modigliani and Modigliani (1997), these portfolios are compared on the same level of risk. The portfolio without cars has a RAP of 5.43%. Solely the Out-of-Sample analysis underperforms with respect to this portfolio. The portfolios consisting of all the risky assets (Eras, Makes and Body Types) performs best, with a RAP of 6.5%, thereby outperforming the portfolio without cars by 1.08% for the same level of risk. Next to that, the portfolio containing the Makes performs second best, having a RAP of 6.15% and thereby outperforming the portfolio including the financial assets only by 0.73%.

Although it might seem interesting to invest in classic cars, it is important to realize that the costs associated with investments in these goods are not incorporated in these returns. The transaction costs, storage costs, insurance costs and all other costs related to investing in cars negatively impact the returns realized on these investments. Therefore, the returns presented in this study need to be considered as the upper-limit and impossible to realize taking into account the costs involved.

To conclude, the personal benefits of investing in a (classic) car can be financial as emotional. Taking into account the costs associated with holding a classic car, it is unlikely that cars outperform equities or bonds. However, using the investments for personal enjoyment, such as using the car for historical events, with the potential of benefitting from financial gains, can make the investment in cars worth it.

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Appendix

Make	Observations
ASA	10
Riley	11
Excalibur	11
Bricklin	11
Panoz	12
Alpine-Renault	12
Tucker 48	12
McLaren	12
Intermeccanica	13
OSCA	13
Frazer	14
Arnolt-Bristol	14
Siata	14
Subaru	15
Acura	15
Mini	15
Bizzarrini	15
Abarth	17
TVR	17
Rambler	18
Lagonda	18
Vauxhall	18
Bristol	20
Nissan	22
Alvis	24
Peugeot	25
Dual-Ghia	25
Rover	26
Nash-Healey	26
Autobianchi	27
Imperial	28
Fiat-Abarth	28
Kaiser	28
Audi	29
Honda	29
Mazda	29
Iso	31
Messerschmitt	31
Bugatti	31
Crosley	32
Talbot-Lago	32
Kaiser-Darrin	33
International	34
Delahaye	38
Amphicar	40
DeLorean	41
Jensen	41
Facel	42
Allard	45
Morgan	46
Volvo	48
GMC	48
Willys	48
Jeep	49
Renault	55

Edsel	58
Daimler	60
Hudson	70
DeSoto	75
Nash	76
Datsun	79
DeTomaso	79
Sunbeam	82
Morris	86
AC	87
Land Rover	100
Austin	101
Toyota	106
Studebaker	122
Citroën	122
AMC	124
Packard	138
Lotus	139
Triumph	186
Lamborghini	208
Lancia	216
Mercury	239
Fiat	264
Lincoln	286
Bentley	293
Maserati	299
Chrysler	304
Rolls-Royce	305
BMW	340
Austin-Healey	351
Oldsmobile	382
Volkswagen	404
MG	417
Alfa Romeo	446
Buick	468
Dodge	494
Cadillac	502
Plymouth	522
Shelby	529
Other makes	747
Pontiac	765
Aston Martin	789
Jaguar	1178
Mercedes-Benz	1188
Porsche	1222
Ferrari	1682
Ford	2131
Chevrolet	4794

Appendix 1. descriptive statistics of all the makes in the dataset.

Appendix 2. This table shows the regression results for the eras regression. The reference category by type of variable is indicated with a # next to the variable. ***, ** and * stand for statistical significance on a 1%, 5% and 10% level respectively.

	Postwar	Y1965Y1974	Modern	Youngtimer	New
VARIABLES	LogPrice	LogPrice	LogPrice	LogPrice	LogPrice
Jan#					

Feb	-0.119***	-0.185***	-0.145**	-0.264***	0.240
Mar	-0.215***	-0.184***	-0.188***	-0.150	0.019
Apr	-0.279***	-0.367***	-0.302***	-0.403***	-0.219
May	-0.198***	-0.176***	-0.064	-0.154	0.214
June	-0.252***	-0.373***	-0.316***	-0.275***	-0.039
July	-0.258***	-0.363***	-0.133	-0.317***	0.093
Aug	0.027	0.015	0.060	-0.029	0.151
Sep	-0.290***	-0.325***	-0.129*	-0.259***	0.122
Oct	-0.286***	-0.211***	-0.174**	-0.250**	-0.208
Nov	-0.153***	-0.271***	-0.356***	-0.371***	-0.224
Dec	-0.185***	-0.309***	-0.165**	-0.303***	-0.193
C1	0.738***	0.836***	0.778***	0.653***	0.251*
C2	0.385***	0.429***	0.427***	0.344***	0.123
C3#					
C4	-0.398***	-0.388***	-0.391***	-0.389***	-1.051*
C5	-0.647***	-0.801***	-0.711***	-0.751**	-1.007**
SilverAuctions#					
ClassicMotorcarAuctions	0.345**	0.083	0.124	0.121	
Brightwells	0.289*	0.812***	0.178	0.705	
TheFinest	0.559***	0.760***	0.227	0.294	0.078
PottsAuctionCompany	0.251	-0.058	0.501**	0.183	
TwinCitiesAuctions	-0.081	0.180	0.164	-0.392	
HollywoodWheels	0.906***	0.641***	0.559**	0.518*	0.330
Vicari	0.319**	0.217*	0.381	0.308	
Shannons	0.600***	0.758***	0.812***	0.628	
Coys	0.831***	0.727***	0.920***	0.723*	0.396
MidAmerica	0.163	0.132	0.130	0.238	1.224
LuckyCollectorCarAuctions	-0.241*	-0.265**	-0.350*	-0.762*	
CollectorCarProductions	0.353***	0.418***	-0.228	-0.623	
Motostalgia	0.618***	0.523***	0.485**	0.040	0.677**
DanKruseClassics	0.106	0.055	0.079	-0.048	0.208
GAA	0.320***	0.358***	0.354**	-0.081	0.321
VanDerBrinkAuctions	-0.221**	-0.230**	-0.085	-0.737*	0.385
Christies	0.875***	0.955***	1.597***	0.517**	0.964
CarlisleEvents	0.367***	0.393***	0.261**	0.139	0.213
Kruse	0.468***	0.401***	0.615***	0.307	0.752
eBay	-0.106	0.141*	0.372***	0.171	0.533*
Leake	0.185**	0.348***	0.391***	0.004	0.721**
TheBransonAuction	0.373***	0.441***	0.452***	0.143	0.358
Silverstone	0.736***	0.845***	0.953***	0.730***	0.402
RMSothebys	1.281***	1.503***	1.815***	1.696***	1.325***
HHAuctioneers	0.365***	0.589***	0.582***	0.371**	0.131
Artcurial	0.886***	1.213***	1.340***	1.181***	0.853**
McCormicks	0.140**	0.211***	0.643***	-0.082	0.090
AuctionsAmerica	0.486***	0.501***	0.306***	0.305**	0.792**
RussoandSteele	0.462***	0.593***	0.625***	0.062	0.760***
WorldwideAuctioneers	0.713***	0.794***	0.786***	0.355**	1.005***
GoodingCo	1.219***	1.317***	1.702***	1.359***	0.931***
BarrettJackson	0.794***	0.777***	0.782***	0.488***	0.737***
MecumAuctions	0.659***	0.695***	0.509***	0.402***	0.639**

RMAuctions	1.027***	0.947***	1.041***	0.980***	1.163***
Bonhams	0.776***	0.884***	1.024***	0.648***	0.754***
OtherAuctions	0.232***	0.227***	0.311***	0.010	-0.039
Onecylinder	-0.662***	-2.205***	-2.283***		4.003**
H12		1.223***	0.993***	-0.413	
H2	-0.235	-0.162	-0.360		
H4	0.112	-0.532***	-0.079	-1.523***	-1.634**
H6	-0.096	0.061	1.218***	1.168***	-0.937
H8	0.702				
I2	-0.338***	0.006	-0.201		2.812*
I3	-0.154	0.471		-0.413	1.890*
I4#					
I5	-0.166	0.462	0.492	0.604	
I6	0.370***	0.452***	0.497***	-0.250	0.292
I8	0.404***	0.940***	0.821	0.217	
Rotary		0.055	0.624	0.462	
V2	0.271	-0.778	-0.915	-0.847	0.477
V4	-0.147	-0.616***	-0.007		
V6	0.269*	0.212***	0.339***	0.404***	0.109
V8	0.460***	0.684***	0.533***	0.161	-0.002
V10	0.521	2.146***	0.689	0.654**	0.117
V12	0.345***	0.658***	0.689***	0.028	0.705
V16	0.071	1.435**	-0.580		2.434**
W12				0.547	0.765
W16					2.007*
Man	0.170***	-1.856*	-1.280**	-0.081	0.137
Auto		-2.228**	-1.600***	-0.511**	0.069
SemiAuto#					
D401150	-0.684***	-0.592***	0.066	-0.494	-5.290***
D11502050	-0.230***	-0.057	0.135	-0.361**	-0.458
D20503050#					
D30504050	0.139***	0.230***	-0.114**	-0.296***	0.211
D40505550	0.315***	-0.028	-0.243***	-0.220*	0.428
D55507050	0.246***	0.182***	0.061	0.018	0.362
D705039000	0.183*	0.203***	0.095	0.580*	0.293
Induction	0.121***	0.105***	-0.026	0.172*	0.046
Odo015000	0.181***	0.144***	0.388***	0.594***	1.545**
Odo1500030000	0.138***	0.161***	0.241***	0.419***	1.127*
Odo3000050000	0.097***	0.132***	0.152***	0.324***	0.902
Odo5000075000	0.063**	0.044*	0.061	0.155*	0.245
Odo75000100000#					
Odo100000	0.201***	0.141***	0.179***	0.331***	1.723***
Buggy	-0.069	0.475			
Conv	0.733***	0.479***	0.505***	0.278***	0.305
Coupe	0.563***	0.272***	0.489***	0.321***	0.689***
Fastback	1.156***	0.367***	0.080		1.054**
Hatchback	0.326	-0.238	0.386***	0.391*	-1.377
Limo	0.352***	0.630***	0.534***	0.572	0.033
Microcar	0.467***	0.069	2.065**		
Pickup	0.173***	-0.288***	0.209*	-0.191	0.360

Racer	1.506***	1.343***	1.584***	1.167***	0.802***
Roadster	1.061***	0.714***	0.390***	0.071	0.642**
SUV	0.157	-0.386***	0.542***	0.011	-0.455
Sedan#					
Targa		-0.127	0.089	0.052	0.800
Tourer	0.013			2.935***	
Utility	0.129	0.006	0.412**	-0.134	
Van	0.896***	0.529***	0.593***	1.112**	
Wagon	0.536***	-0.101	0.374***	0.443	0.021
Beige	-0.127*	-0.114	0.062	-0.052	
Black#					
Blue	0.017	-0.071**	-0.089	-0.117*	0.025
Bronze	-0.021	-0.282***	-0.347**	-0.158	
Brown	-0.246**	-0.216***	-0.132	1.245*	-0.669
Charcoal	-0.593**	-0.182	0.307	-0.680	0.626
Copper	0.010	-0.105	0.144	-0.177	
Cream	-0.076	-0.257***	0.002	-0.181	-0.071
Gold	0.038	-0.125**	-0.192**	-0.197	-0.829*
Green	0.017	-0.115***	-0.081	-0.139	-0.198
Grey	-0.060	-0.180***	-0.098	-0.190	-0.018
Ivory	0.053	-0.004	-0.391		-1.664*
Maroon	0.011	-0.009	-0.074	0.046	0.272
Orange	0.054	-0.005	-0.062	0.160	0.178
Pink	-0.004	-0.054	-0.477	-0.057	-0.436
Primer	-0.703***	0.091			
Purple	-0.060	-0.087	-0.020	0.224	-0.643
Red	-0.028	-0.054*	-0.035	0.030	0.058
Rust	-0.131				
Silver	0.168***	-0.029	-0.064	0.051	0.021
Tan	-0.034	-0.428***	0.214	0.874*	
Turquoise	-0.130**	-0.256**	-0.338	-0.236	0.612
White	0.069**	-0.003	0.083	-0.108	0.125
Yellow	-0.146***	-0.106***	-0.129*	0.169*	-0.250*
ASA	0.568	0.903***			
Riley	0.235	0.329			
Excalibur		-0.627	0.596*	1.739***	
Bricklin		-0.302	-0.232		
Panoz				0.474	-0.653*
McLaren		2.019***		5.216***	2.588***
AlpineRenault	1.507***	0.231	-0.276		
o.Tucker	-	-	-	-	-
OSCA	1.143***	2.615***			
Intermeccanica		-0.720**			
Frazer	0.621***	-0.260			
Siata	0.519**	-0.313			
ArnoltBristol	1.105***				
Mini	1.835**	0.239	0.123	0.979**	
Acura				1.257***	
Bizzarrini		1.240***			
Subaru		-0.855	1.081**	3.497***	0.898

Abarth	0.359	0.070	0.276		
TVR	0.429	-0.117	-0.080	0.633	
Lagonda	0.953***		3.067***		
Vauxhall	-0.078	-0.071	0.553	1.394***	
Rambler	-0.942***	-1.081***			
Bristol	0.785***	0.636	-0.067		
Nissan		-1.266*	1.007**	1.597***	
Alvis	0.038	0.920**			
Peugeot	0.025	-1.128**	0.084	0.848	
DualGhia	0.779***				
NashHealey	0.088				
Rover	-0.522	-0.890***	-0.991*	0.934***	0.775
Autobianchi	-0.440*	-0.346	0.128		
Kaiser	-0.191	0.009			
FiatAbarth	0.548**	0.595	1.627***		
Imperial	-0.229	-0.941***			
Honda		-1.045*	0.533	1.095**	0.498
Mazda			0.199	0.692	
Audi			0.675	0.850	-0.806
Iso	0.264	0.338	0.661		
Messerschmitt	0.815***				
Bugatti	1.579***			2.290***	
TalbotLago	0.807***				
Crosley	-0.223				
KaiserDarrin	0.019				
International	-0.844***	-0.531**	-0.051		0.044
Delahaye	0.813***				
Amphicar	0.596**	1.282***			
DeLorean			0.359**		
Jensen	0.350	-0.145	0.795***	1.580**	
Facel	0.311	0.603			
Allard	0.147			1.621**	
Morgan	0.113	0.439	0.465	2.142***	0.090
GMC	-0.094	-0.187	0.383	0.709**	
Volvo	-0.243	0.063	-0.447	-1.193	
Willys	-0.252**				
Jeep	-0.384	-0.089	-0.074	1.073**	
Renault	-0.180	-0.937***	0.137	-0.108	
Edsel	-0.495***				
Daimler	-0.518***	-0.472	0.903**		
Hudson	0.035				
DeSoto	0.024				
Nash	-0.223**				
DeTomaso		-0.291	1.230**	1.924***	
Datsun	-0.082	-1.851***	0.800**		
Sunbeam	-0.169	-0.119	0.733		
Morris	0.397**	0.512***			
AC	1.045***	1.189***	0.806*	1.903***	
LandRover	0.309*	0.270	0.236	1.584***	1.700
Austin	0.398***	0.251	-0.254	1.721**	

Toyota		-0.580	1.318***	1.441***	
CitroC+n	0.585***	-0.119	0.056	-1.662**	-1.342
Studebaker	-0.576***	-0.131	0.151		
AMC	-0.062	-0.454***	-0.109		
Packard	-0.224***				
Lotus	0.973***	0.464**	0.781***	1.284***	0.626
Triumph	-0.183	-0.476***	0.019		
Lamborghini	0.485	0.759***	2.107***	2.247***	-0.678
Lancia	0.287	0.551**	1.607***	1.560***	
Mercury	-0.245***	-0.508***	-0.453	1.175**	
Fiat	0.044	-0.269	0.204	-0.160	-0.680
Lincoln	-0.121**	-0.512***	-0.395***	0.544*	0.224
Bentley	0.882***	0.618***	0.997***	2.295***	0.567
Maserati	0.616***	0.172	1.190***	0.858*	-0.644
Chrysler	0.095*	-0.736***	-0.528***	-0.430	-1.002**
RollsRoyce	0.794***	0.368**	0.989***	1.873***	-0.074
BMW	0.882***	0.258	0.685**	1.912***	-1.565**
AustinHealey	-0.001	0.252	0.103		
Oldsmobile	-0.105*	-0.321***	-0.248	-0.937	
Volkswagen	-0.211	0.162	0.227	1.374*	-0.050
MG	-0.104	-0.528***	-0.100	0.716*	-0.033
AlfaRomeo	0.073	-0.035	0.508	0.786**	-0.799
Buick	-0.086*	-0.374***	0.353**	-0.506	
Dodge	-0.310***	0.187***	0.168	-1.099***	-0.242
Cadillac	0.191***	-0.665***	-0.038	0.007	0.626
Plymouth	-0.337***	0.288***	0.050	0.461	
Shelby	1.580***	0.827***	0.075	0.889***	-0.152
Pontiac	-0.150***	-0.143***	0.126	-0.078	-0.927**
AstonMartin	1.798***	1.602***	1.700***	2.367***	0.284
Jaguar	0.492***	0.545***	0.349	1.902***	0.366
MercedesBenz	0.964***	0.242	0.405	1.626***	-0.458
Porsche	0.914***	1.184***	0.471*	1.255***	0.449
Ferrari	1.718***	1.135***	1.594***	2.417***	-0.338
Ford	-0.302***	-0.091***	0.168*	0.148	0.635***
OtherMakes	0.473***	0.095	0.460***	1.192***	0.534**
Chevrolet#					
Postwar					
Y1965Y1974					
Modern					
Youngtimer					
New#					
American	-0.195	-0.025	0.095	0.970*	-0.443
British	-0.261*	-0.297*	-0.207	-0.173	-0.688
Italian	0.703***	0.434*	-0.610	0.061	0.807
German	0.174	-0.044	-0.227	0.029	0.870
French	0.362*	0.929***	0.266	0.711	-0.249
Japanese	-0.487	1.257**	-1.126**	-0.016	-0.497
GoodwoodFestivalofSpeed	0.170*	0.199*	0.060	-0.276	1.016**
GoodwoodRevival	0.229**	0.166	0.249	0.850***	-0.236
PebbleBeach	0.289***	0.180*	0.311	0.139	0.392

Constant	8.643***	10.541***	10.368***	9.132***	8.863***
Observations	10,387	9,321	3,138	1,617	630
R-squared	0.724	0.710	0.723	0.782	0.787
Year FE	YES	YES	YES	YES	YES

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Appendix 3. This table shows the regression results for the makes regression. The reference category by type of variable is indicated with a # next to the variable. ***, ** and * stand for statistical significance on a 1%, 5% and 10% level respectively.

	American	British	Italian	German	French	Japanese
VARIABLES	LogPrice	LogPrice	LogPrice	LogPrice	LogPrice	LogPrice
Jan#						
Feb	-0.248***	-0.024	-0.015	-0.208***	-0.079	-0.260
Mar	-0.181***	-0.145***	-0.169**	-0.208***	-0.554**	0.145
Apr	-0.324***	-0.206***	-0.380***	-0.421***	-0.395	-0.128
May	-0.170***	-0.129**	0.028	-0.095	-0.583**	0.036
June	-0.358***	-0.227***	-0.156*	-0.307***	-0.121	-0.494**
July	-0.420***	-0.082	-0.141	-0.173**	-0.165	0.035
Aug	-0.072***	0.163***	0.343***	0.114*	-0.263	-0.114
Sep	-0.300***	-0.125**	-0.138*	-0.339***	-0.339	-0.129
Oct	-0.287***	-0.210***	-0.155*	-0.269***	0.036	-0.135
Nov	-0.278***	-0.114*	-0.011	-0.395***	-0.552	-0.197
Dec	-0.322***	0.020	-0.085	-0.417***	-0.638**	-0.223
C1	0.903***	0.629***	0.726***	0.798***	0.633***	0.911***
C2	0.487***	0.376***	0.318***	0.374***	0.244**	0.406***
C3#						
C4	-0.472***	-0.364***	-0.276***	-0.348***	-0.000	-0.425*
C5	-0.892***	-0.560***	-0.585***	-0.432***	-0.729*	-0.320
SilverAuctions#						
ClassicMotorcarAuctions	0.125	0.865*	0.581	0.375	0.285	
Brightwells	-0.013	0.208	0.370	0.779	-1.226	0.909
TheFinest	0.661**	0.025	0.323	0.699***	0.705	1.333***
PottsAuctionCompany	-0.015	0.377	0.329	0.888***		1.390*
TwinCitiesAuctions	0.274***	-0.684*	-0.291	0.404		1.740***
HollywoodWheels	0.833***	0.202	0.300	0.694***		-0.034
Vicari	0.417***	0.088		0.776*		
Shannons	0.615***	0.607***	0.837**	0.741***		0.589
Coys	0.728***	0.952***	0.937***	0.906***	0.139	
MidAmerica	0.225**	-0.176	0.581	0.034		-0.313
LuckyCollectorCarAuctions	-0.305***	-0.339*	-0.621*	-0.231	-0.100	-0.531
CollectorCarProductions	0.402***	-0.019	-0.288	0.444*		-1.512**
Motostalgia	0.529***	0.282*	0.483	0.450**	0.681	0.464
DanKruseClassics	0.237***	-0.160	-0.421	-0.160		0.563*
GAA	0.451***	-0.022	0.223	0.388*		0.428
VanDerBrinkAuctions	-0.088	-0.317	-0.179	0.235	0.306	-0.111

Christies	0.902***	0.787***	1.291***	1.100***	1.391**	1.497*
CarlisleEvents	0.277***	0.242	0.123	0.350	-0.250	0.057
Kruse	0.329***	0.515***	0.428	0.540***	0.914	2.332***
eBay	0.014	0.267**	0.379	0.618***	0.183	0.670**
Leake	0.491***	-0.108	0.151	0.262*	0.574	0.369
TheBransonAuction	0.428***	0.308***	0.230	0.487***	0.111	-0.063
Silverstone	1.010***	0.508***	0.495**	1.011***	0.635	1.086***
RMSothebys	1.265***	1.095***	1.516***	1.735***	1.309**	1.768***
HHAuctioneers	0.360***	0.354***	0.435*	0.554***	-0.429	0.730**
Artcurial	0.903***	0.823***	1.003***	1.459***	0.879	1.432***
McCormicks	0.197***	0.210*	-0.033	0.621***		0.457
AuctionsAmerica	0.523***	0.306***	0.212	0.610***	0.524	0.411
RussoandSteele	0.589***	0.343***	0.457**	0.602***	0.413	0.644**
WorldwideAuctioneers	0.812***	0.541***	0.727***	0.795***	0.702	0.745**
GoodingCo	1.246***	0.899***	1.588***	1.580***	0.884	0.796*
BarrettJackson	0.801***	0.640***	0.621***	0.806***	0.496	0.531**
MecumAuctions	0.674***	0.288***	0.390	0.594***	0.227	0.695***
RMAuctions	0.922***	0.830***	1.331***	1.223***	1.029*	1.894***
Bonhams	0.708***	0.650***	0.920***	1.059***	0.880	1.030***
OtherAuctions	0.135***	0.396***	1.005***	0.555***	-0.527	0.191
Onecylinder	-2.374***	-0.613*	-0.548	-0.664***	-1.428**	
H4	-1.085***	-0.456*	-0.343	0.215***		0.439
H6	-0.167*	0.744		0.865***		
H8	0.694					
I2	-					
I3	-0.147	0.263		-0.547		-0.367
I4#						
I5	-0.210	0.263	-0.880	0.607**		
I6	0.052	0.087	0.520***	0.441***	-0.279	0.576***
I8	0.049	-0.005	0.684	1.470***	0.457	
V2	0.427	0.090	0.281		-0.277	
V4	0.117	0.460	-0.668***	-0.020	-0.785	
V6	0.371***	0.601***	0.187*	0.303*	-0.260	0.422
V8	0.048	0.053	0.554***	0.407***	0.825*	1.022**
V10	-0.282**	-0.516	0.722**	0.816***	2.395***	2.538***
V12	0.141	0.010	1.195***	0.543***	1.868***	
V16	-0.573	-0.701	1.636***		0.546	
Man	0.318***	-0.306	-0.339*	0.576	0.400	0.331**
SemiAuto#						
D401150	-0.282	-0.840***	-0.619***	-0.391**	-1.024***	0.485
D11502050	0.579***	-0.280***	-0.031	-0.242***	-0.250	0.383**
D20503050#						
D30504050	0.437***	0.350***	-0.357***	0.085	0.314	-0.153
D40505550	0.752***	0.218***	-0.502***	0.011	1.148***	0.168
D55507050	0.792***	0.325***	-0.358***	0.176	0.822*	-0.153
D705039000	0.748***	0.784***	0.631*	0.502	2.084**	
Induction	0.088***	-0.007	-0.005	0.029	-0.031	0.069
Odo015000	0.169***	0.188***	0.357***	0.164***	0.375**	0.196

Odo1500030000	0.113***	0.162***	0.251***	0.134***	-0.208	0.136
Odo3000050000	0.114***	0.096**	0.190***	0.108**	-0.177	0.042
Odo5000075000	0.050**	0.039	0.115**	0.016	-0.209	0.112
Odo750001000000#						
Odo100000	0.210***	0.085**	0.450***	-0.059	0.253	0.171
Buggy	0.664			-0.056		
Conv	0.578***	0.716***	0.349***	0.509***	1.050***	0.117
Coupe	0.391***	0.523***	0.327***	0.562***	0.534***	0.602***
Fastback	0.513***	1.459***	-0.212	1.301**	1.111	0.261
Hatchback	0.572***	0.327*	0.184	0.768***	0.622**	0.259
Limo	0.391***	0.401***	-0.817	0.861***	-1.766*	
Microcar	2.978***	0.102	-0.516	0.322**	-0.574	-0.358
Pickup	0.001	-0.056	0.268	0.630***	-0.837	0.054
Racer	1.184***	1.529***	1.062***	2.066***	1.148***	1.339***
Roadster	1.124***	0.792***	0.535***	1.114***	1.474***	0.311
Sedan#						
SUV	0.298***	0.192	0.240	-0.012	0.538	0.122
Targa	0.546**	0.581	0.210	0.145		-0.173
Tourer	0.109	0.054				
Utility	0.182**	-0.285*	0.086	0.412*	-0.335	0.438
Van	0.445***	0.702***	0.285	0.934***	0.169	
Wagon	0.415***	0.037	-0.084	0.170	0.375	0.096
Beige	-0.186***	0.061	-0.217	0.036	0.012	0.293
Black#						
Blue	-0.063***	0.084**	0.019	-0.157***	-0.106	0.017
Bronze	-0.269***	0.116	-0.235	-0.297	-0.750*	
Brown	-0.287***	-0.082	-0.285	-0.175	0.090	0.475
Charcoal	-0.228	-0.233	0.205	1.896**		
Copper	0.005		-0.133	-0.158	0.318	0.507
Cream	-0.075	-0.094	-0.203	0.006	-0.361	0.381
Gold	-0.029	-0.095	-0.454***	-0.306**	0.151	-0.368
Green	-0.138***	0.064	0.007	-0.164**	-0.138	-0.312
Grey	-0.172***	-0.050	-0.132	-0.071	-0.158	0.241
Ivory	-0.107	0.064	0.317	-0.058	0.227	
Maroon	-0.073*	0.055	0.064	-0.033	0.337	-0.078
Orange	0.012	0.231*	-0.170	-0.077	-0.885	-0.023
Pink	-0.094*	-0.508	0.224	-0.459	0.378	
Primer	0.117	-0.065	-2.121***		-0.390	
Purple	0.038	-0.221*	-0.203	-0.265	-0.097	-1.129
Red	-0.105***	-0.043	0.162***	-0.051	-0.144	-0.064
Rust	-0.237	-1.991***	-0.511		1.378	
Silver	-0.028	0.069	-0.126*	0.233***	-0.242	-0.051
Tan	-0.153**	0.051	0.116	-0.130	0.437	-0.104
Turquoise	-0.215***	0.068	0.314	-0.332*	0.381	
White	-0.010	0.047	0.082	0.065	-0.055	-0.003
Yellow	-0.151***	-0.010	0.087	-0.128	-0.268	-0.122
Excalibur	0.728**					
Panoz	0.364					

Frazer	0.976***					
ArnoltBristol	1.097***					
Rambler	-0.191					
DualGhia	1.481***					
NashHealey	0.573**					
Kaiser	0.504*					
Imperial	0.434					
KaiserDarrin	0.793***					
International	0.074					
DeLorean	1.331***					
GMC	0.574**					
Willys	0.316					
Jeep	0.537**					
Edsel	0.216					
Hudson	0.638**					
DeSoto	0.710***					
Nash	0.130					
Studebaker	0.246					
AMC	0.194					
Packard	0.444*					
Mercury	0.341					
Lincoln	0.445*					
Chrysler	0.629***					
Oldsmobile	0.458*					
Buick	0.512**					
Dodge	0.717***					
Cadillac	0.743***					
Plymouth	0.856***					
Shelby	1.402***					
Pontiac	0.532**					
Ford	0.501**					
Chevrolet	0.601**					
OtherMakes	1.019***	-3.457***	0.382	-0.751***	-0.499	-0.610
Postwar	-0.031	0.804***	0.642***	0.381***	0.930	-0.823
Y1965Y1974	-0.213***	0.517***	0.272**	-0.374***	0.937	-0.400
Modern	-0.810***	0.119	-0.575***	-0.879***	0.475	-1.118***
Youngtimer	-0.850***	0.060	-0.399***	-0.652***	-0.353	-0.512
New#						
GoodwoodFestivalofSpeed	0.080	0.440***	-0.068	0.099	0.180	-0.812
GoodwoodRevival	0.419**	0.197**	0.097	0.382*	-1.617*	0.748
PebbleBeach	0.344***	0.291**	0.042	0.079	0.095	1.432***
I2		-0.711**	-0.098	-0.426	-2.334**	-0.647
W12		0.284	0.249			
Auto		-0.763**	-0.522***	0.242	0.236	
Riley		-3.822***				
Mini		-3.266***				
TVR		-4.326***				
Lagonda		-2.733***				

Vauxhall	-3.726***				
Bristol	-3.018***				
Alvis	-3.652***				
Rover	-3.864***				
Jensen	-3.714***				
Allard	-3.208***				
Morgan	-3.573***				
Sunbeam	-3.853***				
Morris	-3.279***				
AC	-2.623***				
LandRover	-3.300***				
Austin	-3.474***				
Lotus	-3.212***				
Triumph	-4.088***				
Bentley	-2.638***				
RollsRoyce	-2.772***				
AustinHealey	-3.599***				
MG	-3.989***				
AstonMartin	-2.149***				
Jaguar	-3.338***				
H12		0.988***	2.513***		
H2		0.127	-0.536*	0.551*	1.126
ASA		0.735**			
OSCA		1.009***			
Siata		0.361			
Bizzarrini		1.619***			
Abarth		0.170			
Autobianchi		-0.442			
FiatAbarth		0.417			
Iso		0.762***			
DeTomaso		0.457*			
Lamborghini		0.878***			
Lancia		0.548**			
Fiat		-0.178			
Maserati		0.742***			
AlfaRomeo		-0.098			
Ferrari		0.998***			
Rotary			0.356		0.784**
Audi			-0.817**		
Messerschmitt			-0.709***		
Daimler			-1.396***		
BMW			-0.571***		
Volkswagen			-1.235***		
MercedesBenz			-0.518**		
Porsche			-0.565***		
AlpineRenault				0.144	
Peugeot				-0.767*	
Bugatti				0.083	

TalbotLago					-0.553	
Facel					-1.507***	
Renault					-0.769*	
Citroën					-0.791**	
Acura						0.413
Nissan						-0.122
Honda						-0.088
Mazda						-0.896
Datsun						-0.421
Toyota						0.345
Constant	8.031***	12.052***	9.022***	9.435***	9.529***	8.775***
Observations	12,775	4,640	3,427	3,388	405	313
R-squared	0.645	0.714	0.760	0.723	0.834	0.846
Year FE	YES	YES	YES	YES	YES	YES

Standard errors in parentheses

*** p<0.01, ** p<0.05, *p<0.1

Appendix 4. This table shows the regression results for the body types regression. The reference category by type of variable is indicated with a # next to the variable. ***, ** and * stand for statistical significance on a 1%, 5% and 10% level respectively.

	Convertibles	Roadsters	Racers
VARIABLES	LogPrice	LogPrice	LogPrice
Jan#			
Feb	-0.122***	-0.067	-0.051
Mar	-0.124***	-0.163**	-0.407
Apr	-0.264***	-0.252***	-0.296
May	-0.132***	-0.143*	0.427
June	-0.244***	-0.264***	-0.378
July	-0.276***	-0.104	0.492
Aug	-0.078**	0.113*	0.351
Sep	-0.275***	-0.201**	-0.095
Oct	-0.244***	-0.305***	-0.299
Nov	-0.130***	-0.200*	-0.281
Dec	-0.241***	-0.147	0.160
C1	0.782***	0.499***	0.660***
C2	0.435***	0.242***	0.399***
C3#			
C4	-0.377***	-0.307***	-0.480
C5	-0.644***	0.051	-0.371
SilverAuctions#			
ClassicMotorcarAuctions	0.074	1.265	-2.131
Brightwells	0.310	-0.180	-0.830
TheFinest	0.581***	0.522	-0.195
PottsAuctionCompany	0.177	0.496	
TwinCitiesAuctions	-0.049	-0.006	
HollywoodWheels	0.694***	0.423	
Vicari	0.285**	0.503	
Shannons	0.600***	0.777***	

Coys	0.749***	0.625**	0.602
MidAmerica	0.030	-0.084	
LuckyCollectorCarAuctions	-0.493***	-0.278	
CollectorCarProductions	0.186*	-0.123	
Motostalgia	0.550***	0.109	-0.612
DanKruseClassics	-0.025	-0.610**	
GAA	0.285***	-0.229	-0.096
VanDerBrinkAuctions	-0.400***	-1.537***	
Christies	0.849***	0.736***	0.406
CarlisleEvents	0.315***	0.324	
Kruse	0.275***	0.528**	-0.221
eBay	0.192**	0.288*	-0.937
Leake	0.258***	-0.004	-1.561
TheBransonAuction	0.359***	0.354**	
Silverstone	0.802***	0.718***	-0.192
RMSothebys	1.172***	1.280***	0.955
HHAuctioneers	0.435***	0.377**	0.224
Artcurial	1.012***	0.912***	1.258
McCormicks	0.035	0.134	
AuctionsAmerica	0.419***	0.397**	-0.631
RussoandSteele	0.488***	0.385**	-0.542
WorldwideAuctioneers	0.656***	0.574***	-0.273
GoodingCo	1.083***	1.068***	1.036
BarrettJackson	0.665***	0.634***	0.896
MecumAuctions	0.513***	0.600***	-0.350
RMAuctions	0.768***	0.878***	0.878
Bonhams	0.734***	0.748***	0.289
OtherAuctions	0.143**	0.480**	1.972
Onecylinder	-0.857***	-1.807***	-0.890
H2	-0.729**		
H4	-0.032	-0.962***	-0.002
H6	-0.130	-1.457***	0.885**
H8	0.828		
I2	-0.013	-0.538**	-0.670
I4#			
I3	-0.409	-0.683*	
I5	1.199**	-0.373	2.318
I6	0.387***	0.214***	0.292
I8	0.309***	0.471	1.968**
Rotary	0.213		
V2	0.484	-0.007	-0.883
V4	-0.118	-0.985*	0.256
V6	0.401***	0.089	0.187
V8	0.357***	0.139	0.585***
V10	0.776***	0.123	-0.242
V12	0.589***	1.308***	1.009***
V16	-0.411		
W12	0.118	0.345	

W16	-0.035		
Man	0.805	0.808**	-0.276
Auto	0.552	0.548	-0.875*
SemiAuto#			
D401150	-0.591***	-1.039***	-0.489
D11502050	-0.124*	-0.459***	-0.151
D20503050#			
D30504050	0.343***	-0.252***	0.356
D40505550	0.395***	-0.057	0.202
D55507050	0.510***	0.018	-0.100
D705039000	0.537***	-0.385*	-0.382
Induction	0.060**	0.013	-0.205
Odo015000	0.127***	0.154**	1.334***
Odo1500030000	0.110***	0.076	1.178**
Odo3000050000	0.090***	0.032	0.684
Odo5000075000	0.058**	-0.021	0.458
Odo75000100000#			
Odo100000	0.128***	0.145**	1.303***
Beige	-0.044	-0.527	-0.119
Black#			
Blue	-0.085***	0.119*	0.004
Bronze	-0.297***	0.000	
Brown	-0.141*	-0.314	
Charcoal	-0.157	-0.861	
Copper	-0.098	-0.614	
Cream	-0.077	-0.137	0.679
Gold	-0.113**	-0.302*	
Green	-0.081**	0.129*	0.026
Grey	-0.001	-0.006	0.645
Ivory	-0.123	0.094	-0.536
Maroon	-0.051	-0.076	-0.898
Orange	-0.078	-0.333	0.218
Pink	-0.016	-0.141	
Purple	0.156**	-0.134	-1.304
Red	-0.138***	-0.027	0.116
Rust	1.703***	-2.186***	
Silver	0.005	0.140*	0.355
Tan	-0.076	-0.646	
Turquoise	-0.198***	-0.796	
White	-0.040	0.167**	0.074
Yellow	-0.123***	-0.155*	-0.390
Riley	0.225	-0.168	
Excalibur	0.300	1.126	
Panoz	0.400	0.691	
OSCA	0.980	0.416	0.913
Intermeccanica	-0.585	-1.058	
Frazer	-0.491	1.143	3.797**
Siata	-0.529	0.216	

Mini	-0.443		
Acura	0.646		
Bizzarrini	0.765		1.457
TVR	-0.329	-0.095	0.266
Rambler	-1.504*		
Bristol	0.554		
Nissan	1.175		
Alvis	0.405	-0.663	-1.532
Peugeot	-0.812		2.483
DualGhia	0.587		
NashHealey	-0.527	0.067	
Rover	0.404		-0.371
Autobianchi	-0.647		-0.581
Kaiser	0.170	-0.098	
Imperial	-0.288		
Honda	0.490	-1.105	
Mazda	0.016		
Audi	-0.437	-0.005	1.780
Messerschmitt	0.670	0.805	1.506
Bugatti	3.028***	0.288	1.650
TalbotLago	0.390	1.593	1.614
Crosley	-0.359	-0.494	
KaiserDarrin	0.204	-0.244	
Delahaye	0.333	0.870	
Amphicar	0.670		
Jensen	0.351	0.132	
Facel	-0.284		
Allard	0.110	0.384	
Morgan	-0.078	0.022	
Willys	-0.771	-0.877	
Jeep	-0.416		
Renault	-0.330	-0.577	1.435
Edsel	-0.571		
Daimler	-0.485	-1.858*	
Hudson	-0.363		2.976
DeSoto	-0.032		
Nash	-0.670		
Datsun	-0.516	-2.287***	
Sunbeam	-0.138	-0.216	0.737
Morris	-0.013		0.596
AC	0.640	1.053	
LandRover	-0.066		
Austin	0.399	-0.394	-0.095
Citroën	1.039		
Studebaker	-0.691		
AMC	-1.127		-0.757
Packard	-0.246	1.625	
Lotus	0.543	0.266	0.986

Triumph	-0.155	-0.566	0.020
Lamborghini	-0.073	-0.732	-0.451
Lancia	0.215	0.049	0.148
Mercury	-0.638	0.162	1.060
Fiat	-0.365	-0.955	
Lincoln	-0.518	1.736*	-0.307
Bentley	1.252	-0.135	1.980
Maserati	0.187	0.250	1.902
Chrysler	-0.163		
RollsRoyce	1.066		
BMW	0.824	0.510	0.950
AustinHealey	0.223	-0.337	0.554
Oldsmobile	-0.312		
Volkswagen	-0.537	-0.501	
MG	-0.097	-0.446	0.348
AlfaRomeo	-0.462	-1.280	0.530
Buick	-0.196		
Dodge	-0.260	0.698	
Cadillac	-0.068		2.062
Plymouth	-0.098	0.682	2.957*
Shelby	0.680	1.825**	1.031
Pontiac	-0.310	-0.082	0.368
AstonMartin	1.757**	1.811*	0.669
Jaguar	0.295	0.315	1.576
MercedesBenz	0.020	0.312	2.424
Porsche	0.735	1.156	1.648
Ferrari	0.860	0.294	1.584
Ford	-0.535	-0.089	0.924
Chevrolet	-0.193	0.511	0.869
OtherMakes	0.148	0.088	0.806
Postwar	0.855***	0.517***	0.597**
Y1965Y1974	0.519***	-0.127	0.304
Modern	-0.378***	-1.168***	-0.316
Youngtimer	-0.410***	-0.931***	-0.163
American	-0.171	-0.576*	0.121
British	-0.514*	-0.617**	0.416
Italian	0.475*	0.725*	0.504
German	0.124	0.372	0.164
French	0.359	0.526	0.306
Japanese	-0.394	1.164	-1.185
GoodwoodFestivalofSpeed	0.098	0.442**	0.145
GoodwoodRevival	0.189	0.453**	-0.057
PebbleBeach	0.157	0.301**	0.569
Primer		-0.818	
ASA		-0.249	0.754
ArnoltBristol		0.889	
Abarth		-0.776	0.778
Lagonda		-0.458	

Vauxhall		-1.557	0.305
FiatAbarth		-0.089	0.070
GMC		-0.767	
H12			1.508***
McLaren			2.686
AlpineRenault			1.610
Subaru			3.088
Volvo			0.869
DeTomaso			1.176
Toyota			3.383
Provenance			0.210
Winner			0.419***
Podium			0.082
Retired			0.254
FatalAccident			0.943
Replica			-0.681***
FamousOwnerDriver			0.393***
Constant	8.456***	9.575***	8.906***
Observations	7,362	2,355	528
R-squared	0.703	0.779	0.788
Year FE	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 5. This table shows the regression results for the out-of-sample analysis regression. The reference category by type of variable is indicated with a # next to the variable. ***, ** and * stand for statistical significance on a 1%, 5% and 10% level respectively.

	upto2004	Y2010Y2019
VARIABLES	LogPrice	LogPrice
Jan#		
Feb	-0.126***	-0.036
Mar	-0.180***	-0.144*
Apr	-0.379***	-0.367***
May	-0.044	-0.025
June	-0.250***	-0.190**
July	-0.349***	-0.113
Aug	0.031	0.407***
Sep	-0.417***	-0.144
Oct	-0.195***	-0.210**
Nov	-0.174***	-0.005
Dec	-0.248***	-0.126
C1	0.912***	0.786***
C2	0.454***	0.320***
C3#		
C4	-0.414***	-0.233**
C5	-0.773***	-0.615***
SilverAuctions#		
ClassicMotorcarAuctions		0.352

Brightwells		0.478
TheFinest		0.161
TwinCitiesAuctions		-0.828
HollywoodWheels		0.289
Shannons	0.543***	0.411
Coys	0.950***	0.759
LuckyCollectorCarAuctions		-0.780
CollectorCarProductions		-0.356
Motostalgia		0.172
DanKruseClassics		-0.295
GAA		0.103
Christies	0.900***	0.882*
CarlisleEvents	0.179***	0.080
Kruse	0.304***	0.346
eBay	0.206***	0.709
Leake		0.048
TheBransonAuction	0.464***	-0.015
Silverstone		0.393
RMSothebys		1.444***
HHAuctioneers	0.227***	0.581
Artcurial	0.774***	0.818
McCormicks	0.122*	-0.396
AuctionsAmerica	0.312***	-0.035
RussoandSteele	0.533***	0.162
WorldwideAuctioneers	0.651***	0.556
GoodingCo	1.007***	1.441***
BarrettJackson	0.746***	0.271
MecumAuctions	0.521***	0.292
RMAuctions	0.769***	1.302***
Bonhams	0.622***	0.811*
OtherAuctions	0.305***	1.021**
H12	0.453***	0.038
I2	-0.048	0.212
I4#		
I5	0.264	-0.399
I6	0.441***	-0.132
I8	0.719***	-0.030
V2	-0.327	-0.060
V4	-0.409**	-1.588*
V6	0.387***	-0.487***
V8	0.538***	-0.178
V10	0.504**	0.701
V12	0.736***	0.182
V16	0.845**	0.960*
W12		-0.801
W16		0.201
Man	0.164	-0.073
Auto	-0.176	-0.268

SemiAuto#		
D401150	-0.274***	-0.913
D11502050	-0.136**	0.002
D20503050		
D30504050	0.098**	-0.029
D40505550	0.096**	-0.171***
D55507050	0.233***	0.179
D705039000	0.252***	0.064
Induction	0.050**	0.315***
Odo015000	0.203***	0.275***
Odo1500030000	0.147***	0.132*
Odo3000050000	0.122***	0.158**
Odo5000075000	0.060**	0.075
Odo75000100000#		
Odo100000	0.204***	0.315***
Conv	0.601***	0.501***
Coupe	0.433***	0.183
Hatchback	-0.058	-0.286
Sedan#		
Racer	0.990***	0.465**
Roadster	0.912***	0.456***
Targa	0.128	0.050
Wagon	0.335***	0.351
Beige	-0.080	-0.680
Black#		
Blue	-0.070**	0.015
Bronze	-0.147	-0.002
Brown	-0.311***	-0.077
Charcoal	0.021	0.223
Copper	0.110	-0.014
Cream	-0.216***	-0.189
Gold	-0.189***	-0.283
Green	-0.136***	0.074
Grey	-0.140**	-0.063
Ivory	-0.078	0.711*
Maroon	-0.087	-0.010
Orange	0.020	-0.199
Pink	-0.114	0.555
Primer	-1.434***	-1.356**
Purple	-0.069	-0.075
Red	-0.081***	0.181***
Silver	-0.035	0.023
Tan	-0.045	0.905
Turquoise	-0.152*	0.399
White	-0.039	0.099
Yellow	-0.082**	0.070
Bizzarrini	1.377***	0.891**
Lagonda	1.600***	-2.836***

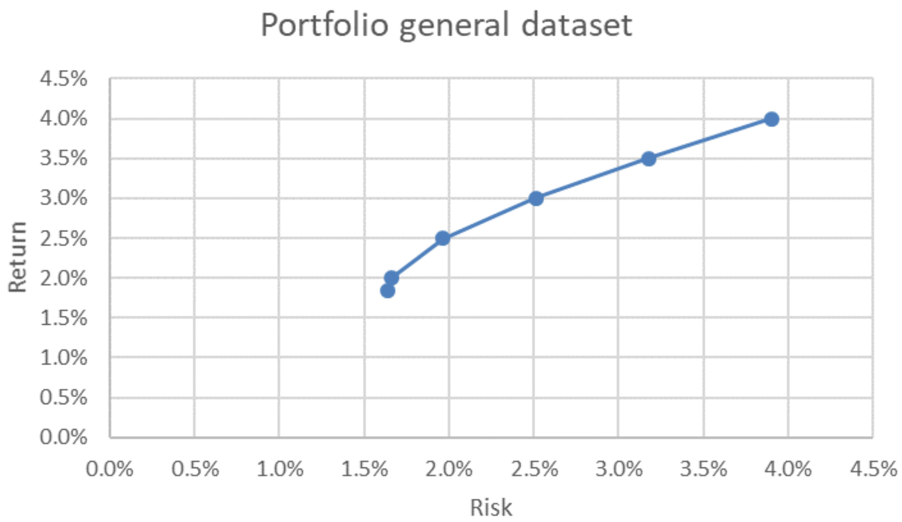
Bugatti	1.320***	-1.007***
AstonMartin	1.218***	-1.819***
Ferrari	1.230***	0.634**
Postwar	0.110	1.100***
Y1965Y1974	-0.256***	0.737***
Modern	-0.891***	-0.161
Youngtimer	-0.702***	-0.085
New#		
Italian	-0.090	-2.357***
GoodwoodFestivalofSpeed	0.119	0.116
GoodwoodRevival	0.331***	0.178
PebbleBeach	0.154	0.070
Provenance	0.861***	0.504**
Winner	0.407***	0.374
Podium	-0.311	0.349
FatalAccident	1.490**	1.530*
Replica	-0.409***	-0.812***
FamousOwnerDriver	0.536***	0.239
PottsAuctionCompany	0.088	
MidAmerica	0.106	
VanDerBrinkAuctions	-0.369**	
Onecylinder	-0.581***	
H2	-0.481**	
H4	-0.173**	
H6	0.083	
I3	-1.378***	
Rotary	1.051*	
Buggy	-0.195	
Fastback	0.588***	
Limo	0.327***	
Microcar	0.857	
Pickup	-0.104	
SUV	0.168	
Tourer	-0.648	
Utility	0.196	
Van	0.619***	
Rust	-0.891*	
ASA	0.311	
Riley	0.275	
Excalibur	0.370	
Bricklin	-0.398	
Panoz	-0.211	
McLaren	3.861***	
AlpineRenault	0.287	
OSCA	1.982***	
Intermeccanica	-0.167	
Frazer	0.837**	
Siata	0.836	

ArnoltBristol	0.616**
Mini	0.573
Acura	0.073
Subaru	-0.778
Abarth	0.468
TVR	-0.370
Vauxhall	0.066
Rambler	-0.990***
Bristol	0.617**
Alvis	-0.055
Peugeot	-0.202
DualGhia	0.799***
NashHealey	0.072
Rover	-0.156
Autobianchi	-0.316
Kaiser	-0.244
FiatAbarth	0.685**
Honda	-0.898
Mazda	-1.404
Audi	0.668
Iso	0.424
Messerschmitt	0.272
TalbotLago	0.545*
Crosley	-0.874***
KaiserDarrin	0.064
International	-1.129***
Delahaye	0.526
Amphicar	0.568**
DeLorean	0.239
Jensen	0.104
Facel	-0.225
Allard	0.350
Morgan	0.082
GMC	0.347
Volvo	-0.201
Willys	-0.736***
Jeep	-0.081
Renault	-0.284
Edsel	-0.445***
Daimler	-0.016
Hudson	0.041
DeSoto	-0.082
Nash	-0.387***
DeTomaso	0.120
Datsun	-1.289*
Sunbeam	-0.431**
Morris	0.056
AC	0.674***

LandRover	0.348	
Austin	0.047	
Toyota	0.025	
CitroÃ«n	0.551**	
Studebaker	-0.516***	
AMC	-0.346***	
Packard	-0.112	
Lotus	0.757***	
Triumph	-0.218	
Lamborghini	0.895***	
Lancia	0.742***	
Mercury	-0.181**	
Fiat	-0.063	
Lincoln	-0.187**	
Bentley	0.823***	
Maserati	0.481**	
Chrysler	0.020	
RollsRoyce	0.842***	
BMW	0.252	
AustinHealey	-0.126	
Oldsmobile	-0.123*	
Volkswagen	-0.157	
MG	-0.220*	
AlfaRomeo	0.186	
Buick	-0.041	
Dodge	0.187***	
Cadillac	0.008	
Plymouth	0.402***	
Shelby	1.014***	
Pontiac	-0.046	
Jaguar	0.338***	
MercedesBenz	0.355**	
Porsche	0.680***	
Ford	-0.185***	
OtherMakes	0.257***	
American	-0.130	
British	-0.338*	
German	-0.037	
French	0.338	
Japanese	0.702	
Retired	-0.049	
Constant	8.883***	11.682***
Observations	8,801	2,560
R-squared	0.690	0.668
Year FE	YES	YES

Standard errors in parentheses

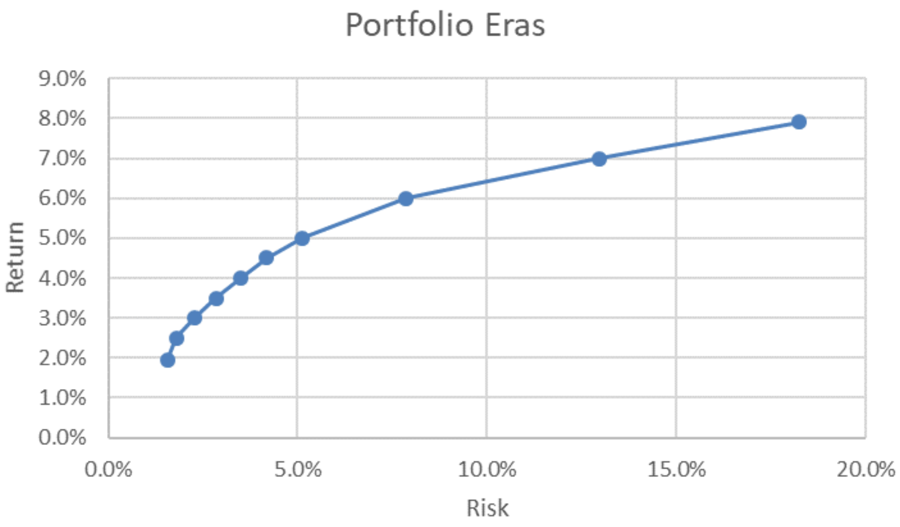
*** p<0.01, ** p<0.05, * p<0.1



Appendix 6. Optimal portfolio comprising of the financial assets and the whole dataset of cars.

Return	Standard Deviation	MSCI World Stock	Risk Free Rate	FTSE World Government Bond	General	Total
1.8%	1.6%	2.2%	92.1%	3.2%	2.5%	100.0%
2.0%	1.7%	3.2%	87.6%	6.5%	2.6%	100.0%
2.5%	2.0%	6.3%	73.9%	16.8%	3.1%	100.0%
3.0%	2.5%	9.3%	60.1%	27.1%	3.5%	100.0%
3.5%	3.2%	12.4%	46.4%	37.4%	3.9%	100.0%
4.0%	3.9%	15.4%	32.6%	47.7%	4.3%	100.0%
4.5%	4.7%	18.4%	18.9%	57.9%	4.8%	100.0%
5.0%	5.4%	21.5%	5.1%	68.2%	5.2%	100.0%
5.5%	6.3%	26.9%	0.0%	73.1%	0.0%	100.0%
6.0%	7.9%	42.1%	0.0%	57.9%	0.0%	100.0%
6.5%	10.2%	57.3%	0.0%	42.7%	0.0%	100.0%
7.0%	13.0%	72.5%	0.0%	27.5%	0.0%	100.0%
7.5%	15.8%	87.7%	0.0%	12.3%	0.0%	100.0%
7.9%	18.2%	100.0%	0.0%	0.0%	0.0%	100.0%

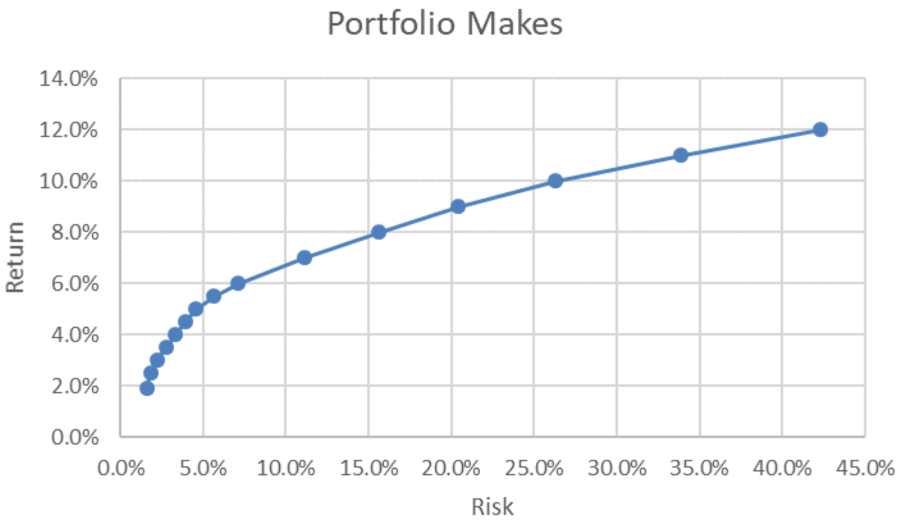
Appendix 7. The weights allocated to each asset for a target return while minimizing the standard deviation of the portfolio.



Appendix 8. Optimal portfolio comprising of the financial assets and the cars based on Eras.

Return	Risk	MSCI World Stock	Risk Free Rate	FTSE World Government Bond	1947-1964	1965-1974	1975-1989	1990-2003	2004-2019	Total
1.9%	1.6%	2.5%	84.8%	6.6%	0.0%	2.9%	3.2%	0.0%	0.0%	100.0%
2.5%	1.8%	5.5%	66.1%	19.3%	0.0%	4.0%	4.7%	0.0%	0.3%	100.0%
3.0%	2.3%	7.6%	48.0%	30.6%	2.0%	4.6%	5.6%	0.0%	1.6%	100.0%
3.5%	2.9%	9.4%	29.0%	42.1%	5.5%	4.8%	6.1%	0.0%	3.1%	100.0%
4.0%	3.5%	11.1%	10.0%	53.6%	9.0%	5.0%	6.6%	0.0%	4.7%	100.0%
4.5%	4.2%	14.8%	0.0%	61.7%	9.1%	4.1%	5.3%	0.0%	5.0%	100.0%
5.0%	5.1%	20.5%	0.0%	66.1%	5.3%	2.2%	2.0%	0.0%	3.9%	100.0%
6.0%	7.9%	42.1%	0.0%	57.9%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%
7.0%	13.0%	72.5%	0.0%	27.5%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%
7.9%	18.2%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%
3.5%	9.5%	0.0%	0.0%	0.0%	12.2%	54.5%	0.0%	0.0%	33.3%	100.0%
4.0%	13.2%	0.0%	0.0%	0.0%	0.0%	43.3%	0.0%	0.0%	56.7%	100.0%
4.5%	20.6%	0.0%	0.0%	0.0%	0.0%	3.2%	0.0%	8.5%	88.2%	100.0%
4.6%	22.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%	100.0%

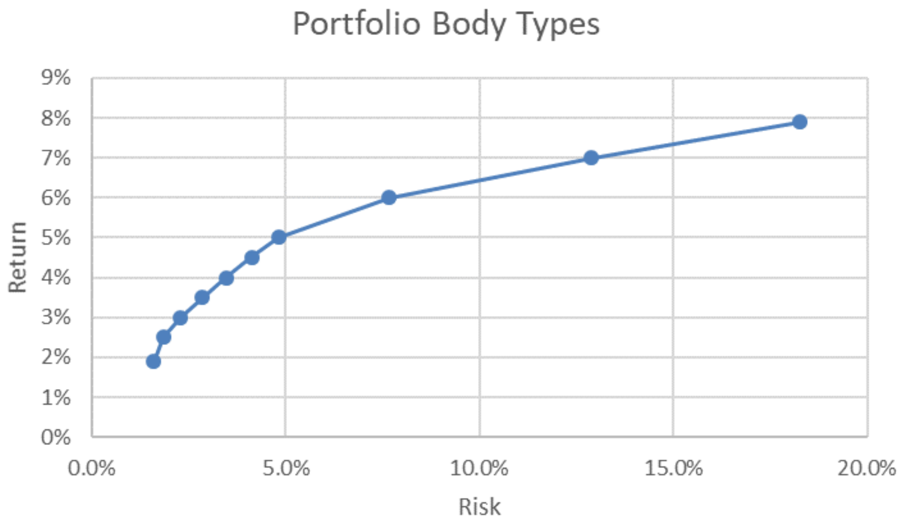
Appendix 9. The weights allocated to each asset for a target return while minimizing the standard deviation of the portfolio.



Appendix 10. Optimal portfolio comprising of the financial assets and the cars based on country of make.

Return	Risk	MSCI World Stock	Risk Free Rate	FTSE World Government Bond	American	British	Italian	German	French	Japanese	Total
1.9%	1.6%	3.0%	91.6%	2.6%	1.3%	0.0%	0.0%	0.0%	1.5%	0.0%	100.0%
2.5%	1.8%	6.7%	75.6%	12.9%	0.0%	0.0%	0.0%	2.4%	2.4%	0.0%	100.0%
3.0%	2.2%	9.7%	59.5%	21.9%	0.0%	0.0%	0.0%	6.0%	2.9%	0.0%	100.0%
3.5%	2.7%	12.7%	43.5%	30.9%	0.0%	0.0%	0.0%	9.7%	3.3%	0.0%	100.0%
4.0%	3.3%	15.6%	27.4%	39.9%	0.0%	0.0%	0.0%	13.3%	3.8%	0.0%	100.0%
4.5%	3.9%	18.6%	11.3%	48.9%	0.0%	0.0%	0.0%	16.9%	4.3%	0.0%	100.0%
5.0%	4.6%	22.7%	0.0%	55.4%	0.0%	1.0%	0.0%	15.5%	5.3%	0.0%	100.0%
5.5%	5.7%	26.8%	0.0%	54.4%	0.0%	7.7%	1.2%	2.7%	7.3%	0.0%	100.0%
6.0%	7.1%	33.6%	0.0%	48.6%	0.0%	6.0%	4.0%	0.0%	7.9%	0.0%	100.0%
7.0%	11.1%	48.1%	0.0%	33.1%	0.0%	0.0%	10.6%	0.0%	8.2%	0.0%	100.0%
8.0%	15.6%	61.4%	0.0%	12.8%	0.0%	0.0%	17.8%	0.0%	8.0%	0.0%	100.0%
9.0%	20.4%	70.3%	0.0%	0.0%	0.0%	0.0%	26.5%	0.0%	3.2%	0.0%	100.0%
10.0%	26.3%	54.2%	0.0%	0.0%	0.0%	0.0%	45.8%	0.0%	0.0%	0.0%	100.0%
11.0%	33.9%	32.3%	0.0%	0.0%	0.0%	0.0%	67.7%	0.0%	0.0%	0.0%	100.0%
12.0%	42.3%	10.4%	0.0%	0.0%	0.0%	0.0%	89.6%	0.0%	0.0%	0.0%	100.0%
12.5%	46.4%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%	0.0%	0.0%	0.0%	100.0%

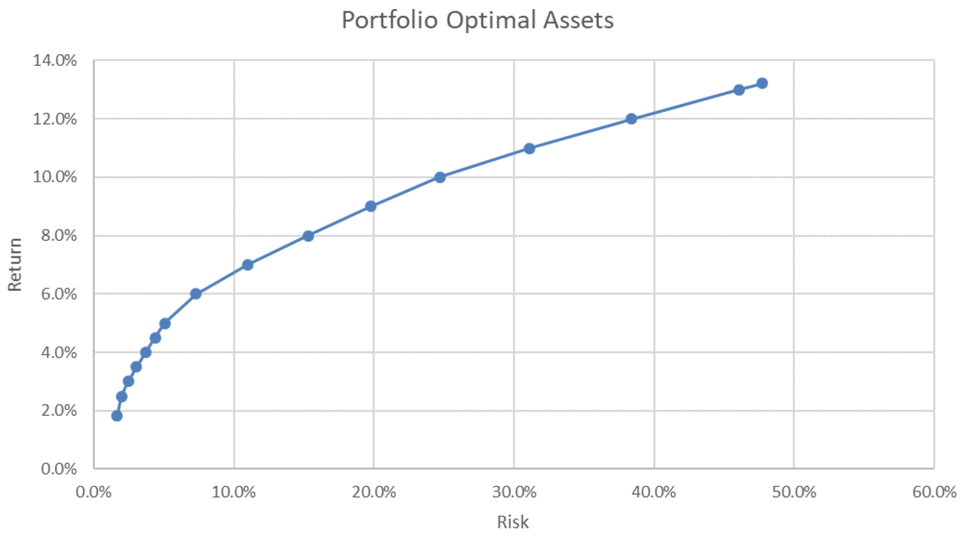
Appendix 11. The weights allocated to each asset for a target return while minimizing the standard deviation of the portfolio.



Appendix 12. Optimal portfolio comprising of the financial assets and the cars based on body type (convertibles, roadsters and racers)

Return	Standard Deviation	MSCI World Stock	Risk Free Rate	FTSE World Government Bond	Convertibles	Roadsters	Racers	Total
1.9%	1.6%	2.4%	93.0%	3.1%	0.2%	0.0%	1.3%	100.0%
2.5%	1.8%	5.1%	75.1%	14.8%	0.0%	2.9%	2.2%	100.0%
3.0%	2.3%	7.0%	59.5%	24.4%	0.0%	6.2%	2.9%	100.0%
3.5%	2.8%	8.9%	43.9%	34.0%	0.0%	9.4%	3.7%	100.0%
4.0%	3.5%	10.9%	28.4%	43.7%	0.0%	12.7%	4.4%	100.0%
4.5%	4.1%	12.8%	12.8%	53.3%	0.0%	15.9%	5.1%	100.0%
5.0%	4.8%	16.3%	0.0%	61.7%	0.0%	16.3%	5.7%	100.0%
6.0%	7.7%	41.4%	0.0%	53.2%	0.0%	0.0%	5.4%	100.0%
7.0%	12.9%	72.0%	0.0%	23.7%	0.0%	0.0%	4.4%	100.0%
7.9%	18.2%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%

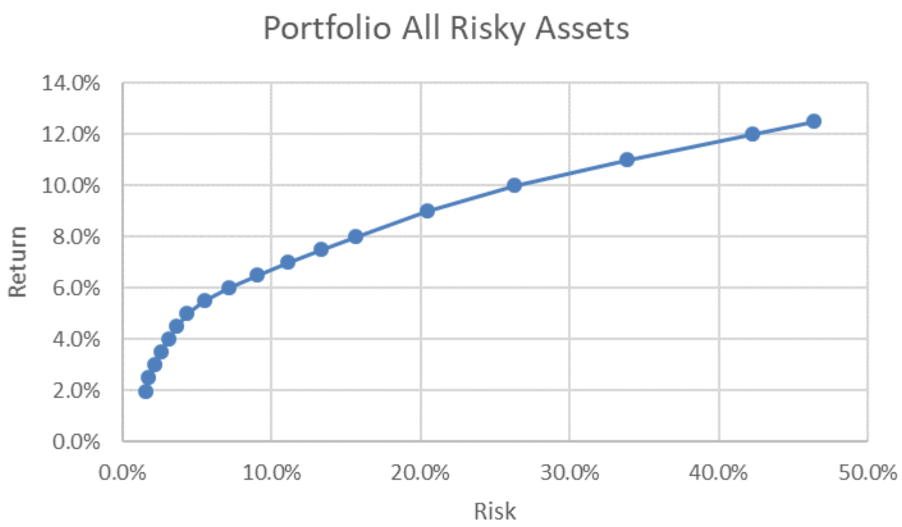
Appendix 13. The weights allocated to each asset for a target return while minimizing the standard deviation of the portfolio.



Appendix 14. Optimal portfolio comprising of the financial assets and the optimal assets (roadsters, Italian – and British cars).

Return	Risk	MSCI World Stock	Risk Free Rate	FTSE World Government Bond	British	Italian	Roadsters	Total
1.8%	1.7%	2.2%	95.5%	2.1%	0.0%	0.2%	0.0%	100.0%
2.5%	2.0%	5.8%	76.0%	15.5%	0.7%	0.0%	2.0%	100.0%
3.0%	2.5%	7.9%	60.9%	24.8%	2.0%	0.0%	4.3%	100.0%
3.5%	3.1%	10.0%	45.9%	34.1%	3.4%	0.0%	6.6%	100.0%
4.0%	3.7%	12.1%	31.0%	43.3%	4.8%	0.0%	8.8%	100.0%
4.5%	4.4%	14.3%	16.0%	52.6%	6.2%	0.0%	11.0%	100.0%
5.0%	5.1%	16.4%	1.0%	61.8%	7.6%	0.0%	13.3%	100.0%
6.0%	7.3%	28.9%	0.0%	53.4%	13.1%	4.7%	0.0%	100.0%
7.0%	11.0%	41.2%	0.0%	35.6%	11.6%	11.7%	0.0%	100.0%
8.0%	15.3%	53.5%	0.0%	17.8%	10.1%	18.6%	0.0%	100.0%
9.0%	19.7%	65.8%	0.0%	0.0%	8.6%	25.6%	0.0%	100.0%
10.0%	24.7%	60.5%	0.0%	0.0%	0.0%	39.5%	0.0%	100.0%
11.0%	31.1%	41.7%	0.0%	0.0%	0.0%	58.3%	0.0%	100.0%
12.0%	38.4%	22.8%	0.0%	0.0%	0.0%	77.2%	0.0%	100.0%
13.0%	46.1%	4.0%	0.0%	0.0%	0.0%	96.0%	0.0%	100.0%
13.2%	47.8%	0.0%	0.0%	0.0%	0.0%	100.0%	0.0%	100.0%
9.0%	24.3%	0.0%	0.0%	0.0%	50.4%	49.6%	0.0%	100.0%
10.0%	29.6%	0.0%	0.0%	0.0%	38.5%	61.5%	0.0%	100.0%
11.0%	35.2%	0.0%	0.0%	0.0%	26.5%	73.5%	0.0%	100.0%
12.0%	40.8%	0.0%	0.0%	0.0%	14.5%	85.5%	0.0%	100.0%
13.0%	46.5%	0.0%	0.0%	0.0%	2.5%	97.5%	0.0%	100.0%
13.2%	47.8%	0.0%	0.0%	0.0%	0.0%	100.0%	0.0%	100.0%

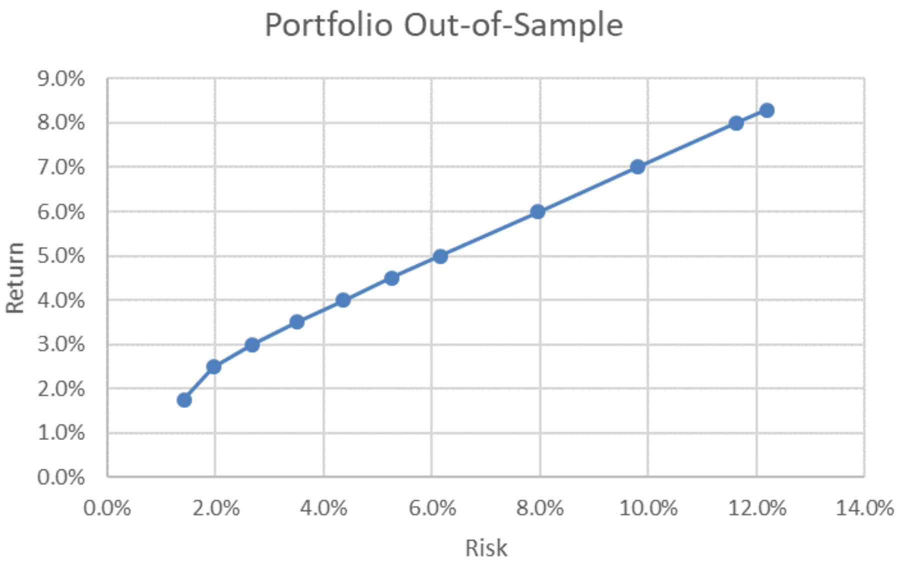
Appendix 15. The weights allocated to each asset for a target return while minimizing the standard deviation of the portfolio.



Appendix 16. Optimal portfolio comprising of the financial assets and the optimal assets (roadsters, Italian – and British cars).

Return	Risk	MSCI Wor	Risk Free F	FTSE Worl	American	British	Italian	German	French	Japanese	1947-1964	1965-1974	1975-1989	1990-2003	2004-2019	Convertibl	Roadsters	Racers	Total
2.0%	1.5%	2.7%	85.2%	6.3%	0.0%	0.0%	0.0%	0.0%	0.4%	0.0%	0.0%	2.4%	2.6%	0.0%	0.0%	0.0%	0.0%	0.5%	100.0%
2.5%	1.7%	5.3%	69.6%	15.8%	0.0%	0.0%	0.0%	1.3%	1.4%	0.0%	0.0%	2.4%	2.4%	0.0%	1.1%	0.0%	0.0%	0.7%	100.0%
3.0%	2.1%	6.9%	53.8%	23.6%	0.0%	0.0%	0.0%	4.8%	2.2%	0.0%	2.2%	1.5%	0.6%	0.0%	3.0%	0.0%	0.0%	1.4%	100.0%
3.5%	2.6%	8.6%	36.3%	32.6%	0.0%	0.3%	0.0%	7.4%	2.9%	0.0%	4.3%	1.0%	0.0%	0.0%	4.8%	0.0%	0.0%	1.9%	100.0%
4.0%	3.1%	10.4%	18.2%	42.1%	0.0%	0.6%	0.0%	9.8%	3.5%	0.0%	6.0%	0.8%	0.0%	0.0%	6.3%	0.0%	0.0%	2.3%	100.0%
4.5%	3.6%	12.2%	0.2%	51.5%	0.0%	0.9%	0.0%	12.3%	4.1%	0.0%	7.7%	0.6%	0.0%	0.0%	7.9%	0.0%	0.0%	2.7%	100.0%
5.0%	4.3%	16.8%	0.0%	51.6%	0.0%	7.6%	0.5%	8.3%	6.2%	0.0%	0.0%	0.0%	0.0%	0.0%	7.2%	0.0%	0.0%	1.8%	100.0%
5.5%	5.5%	23.0%	0.0%	49.7%	0.0%	10.4%	2.1%	0.0%	8.1%	0.0%	0.0%	0.0%	0.0%	0.0%	6.0%	0.0%	0.0%	0.6%	100.0%
6.0%	7.1%	32.6%	0.0%	46.7%	0.0%	6.2%	4.4%	0.0%	8.2%	0.0%	0.0%	0.0%	0.0%	0.0%	1.9%	0.0%	0.0%	0.0%	100.0%
6.5%	9.0%	41.0%	0.0%	41.5%	0.0%	2.1%	7.2%	0.0%	8.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%
7.0%	11.1%	48.1%	0.0%	33.1%	0.0%	0.0%	10.6%	0.0%	8.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%
7.5%	13.3%	54.8%	0.0%	22.9%	0.0%	0.0%	14.2%	0.0%	8.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%
8.0%	15.6%	61.4%	0.0%	12.8%	0.0%	0.0%	17.8%	0.0%	8.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%
9.0%	20.4%	70.3%	0.0%	0.0%	0.0%	0.0%	26.5%	0.0%	3.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%
10.0%	26.3%	54.2%	0.0%	0.0%	0.0%	0.0%	45.8%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%
11.0%	33.9%	32.3%	0.0%	0.0%	0.0%	0.0%	67.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%
12.0%	42.3%	10.4%	0.0%	0.0%	0.0%	0.0%	89.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%
12.5%	46.4%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%

Appendix 17. The weights allocated to each asset for a target return while minimizing the standard deviation of the portfolio.



Appendix 18. Optimal portfolio comprising of the financial assets and the Out-of-Sample analysis.

Return	Standard Deviation	MSCI World Stock	Risk Free Rate	FTSE World Government Bond	Out-of-Sample analysis	Total
1.8%	1.4%	7.1%	92.3%	0.0%	0.6%	100.0%
2.5%	2.0%	18.0%	82.0%	0.0%	0.0%	100.0%
3.0%	2.7%	25.1%	74.9%	0.0%	0.0%	100.0%
3.5%	3.5%	32.1%	67.9%	0.0%	0.0%	100.0%
4.0%	4.4%	39.2%	60.8%	0.0%	0.0%	100.0%
4.5%	5.3%	46.3%	53.7%	0.0%	0.0%	100.0%
5.0%	6.1%	53.3%	46.7%	0.0%	0.0%	100.0%
6.0%	8.0%	67.5%	32.5%	0.0%	0.0%	100.0%
7.0%	9.8%	81.6%	18.4%	0.0%	0.0%	100.0%
8.0%	11.6%	95.7%	4.3%	0.0%	0.0%	100.0%
8.3%	12.2%	100.0%	0.0%	0.0%	0.0%	100.0%

Appendix 19. The weights allocated to each asset for a target return while minimizing the standard deviation of the portfolio.