Collector cars; childhood dream or sound investment opportunity?

-hedonic regression analysis of the collector car market-

[The main question of this study is whether collector cars can be considered as a viable investment opportunity. In order to answer that question, first this study tries to identify the relevant variables that determine sale prices of collector cars at auctions. Second, it creates a price index on collector cars through hedonic regression analysis on data from 1,200 cars sold on auction between 1996 and 2011. Ultimately it will compare the resulting collector car index with indices on other assets and look at the potential of collector cars to be part of investment portfolios to answer the main question. The study concludes that, with some limitations, collector cars can be regarded as viable investment opportunities]

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Preface

Ever since Karl Benz built his first 'motorwagen' in 1885, cars have been the object of many people's desires. Nowadays, Benz' 1885 creation, sporting just under one horsepower, may seem far removed from the latest iteration of Bugatti's EB 16.4 Veyron, the Veyron Super Sport with twelve hundred horsepower on the spec sheet and to many accounts, a couple more in reality. However, despite the fact that cars have evolved to become ever faster, better and stronger, you will be able to find highly valued specimen today from any of the decades the car has been in existence, some of which worth considerably more now than what they originally listed for when they were new.

Originally intended to first and foremost be a means of transportation, cars quickly became much more than a carriage that could somehow move without being attached to a horse. Soon people started to race against each other, on public roads but also on some of the first purpose built racetracks like Brooklands (1906) and Indianapolis Motor Speedway (1909) making the races a bit safer, or at least safer for the innocent bystanders. The car became a status symbol for individuals, but also a matter of national pride for countries whose sometimes unsavory governments invested heavily in their native car companies' racing activities. Their aim was to show off the nation's technical prowess and superiority over other nations by beating the best cars that competing manufacturers from foreign nations could come up with. Consequently, winning races didn't hurt the brand value and recognition of the manufacturers either, which lead to the popular adage 'win on Sunday, sell on Monday'. The resulting emergence of the car as a prestige object opened up the market for manufacturers from the likes of Duesenberg, Rolls Royce, Bentley and Daimler-Benz to offer ever more luxurious, more powerful, more beautiful and as a result increasingly expensive automobiles.

Over the years, some cars have become icons of different eras, renowned for their success on the race track, or just their beauty, their rarity and sometimes something else altogether. Some might even be considered art, as Malcolm Rogers, director of the Museum of Fine Arts in Boston notes:

"These cars - with their exquisite line and innovative designs – are works of art, and their designers are artists."

Unsurprisingly, the desirability of these cars has led not only to the creation of private and public car collections all over the world, but also to collector cars being traded through auctions, much like art. Some of the traditional art auction houses like Christie's, Bonham's and Sotheby's got involved and have now been joined and sometimes surpassed by newer auction houses catering solely to the collector car market, like RM Auctions, Barret-Jackson and Gooding & Company. To illustrate; In the last 12 months alone, 65 over 1-million dollar sales for single cars have been recorded, including the most expensive car ever to be sold at an auction, a 1936 Bugatti Type 57SC Atlantic, sold at over 30 million US dollars.

In the light of anecdotal evidence seemingly suggesting investing in collector cars can deliver benefits aside from enjoyment, this study tries to delve deeper in to the subject of what determines prices in the collector car market. It will do so using hedonic regression analysis on collected auction data to identify what factors are the important price determinants of a collector car. The hedonic regression analysis will also be used to create a collector cars price index (CCI) for the last 16 years in order to compare investing in collector cars to more traditional investment opportunities and to explore the viability of investing in collector cars as a tool for portfolio diversification. Ultimately, the aim of this study is to try and find the answer to the question if investing in collector cars can be more than just the realization of a childhood dream.

1. Literature Review

1.1 Collector Car Returns

Review of existing literature on collector car returns and the viability of collector cars as an investment asset reveals that little research has been done on this particular topic. Many reports have shown up on internet sites, in magazines in newspapers and even on CNN about the monetary benefits of investing in sports cars, but these have mostly been based on anecdotal evidence instead of structured study. Only recently it seems there has been more interest in this field, quite possibly motivated by some of the spectacular sales results that have been covered in the media as of late.

A study by van Bergen (van Bergen, 2009) on the viability of classic Ferrari as a financial instrument found an average annualized return of 1.65% for classic Ferrari sold between 1989 and 2008, based on 640 auction results of 21 selected Ferrari models built between 1950 and 1970. Furthermore, it found the market in classic Ferrari is extremely volatile and has little correlation to more traditional assets. The study concludes that because of the negative correlation with traditional assets and potentially high rewards resulting from the volatility of the returns, classic Ferrari have potential to serve as a sound addition to diversify one's investment portfolio.

Another noteworthy development in this field is an initiative by 'The Historic Automobile Group' or HAGI (http://www.historicautogroup.com/) founded in 2007, that tries to take an academic approach to create price indices for several subsections of the collector car market. As of December 2008, HAGI uses a proprietary market capitalization formula to create four separate indices for 'exceptional historic automobiles', 'exceptional historic automobiles excluding Ferrari and Porsche', 'rare Ferrari' and 'rare Porsche', respectively, all based on data from private contacts, marque specialists, dealers and auction results. The price index is constructed using a chained Paasche method on monthly sales data on certain car models that are designated by a special committee. It will be interesting to see in what direction these indices will go in the future.

1.2 Hedonic Regression and the Collector Car Market

Hedonic regression controls for quality changes in the transacted goods by attributing implicit prices to their ‘utility-bearing characteristics (Rosen, 1974). While this method was popularized in the early 1960s by Griliches (1961), it was pioneered by Court in 1939 (Goodman 1998). Court was an economist for the Automobile Manufacturers’ Association in Detroit interested in automobile price indices. He felt that the price index procedures used at the time were too simple and therefore inadequate, noting that passenger cars serve so many different purposes that to value a car by just a single, most important specification was not a true reflection of a car’s worth. Instead, he set out to “combine several specifications to form a single composite measure” and coined the term ‘hedonic’ to describe the weighting of the relative importance of various components. In his model he used the variables horsepower, wheelbase and weight in order to construct an index of ‘usefulness and desirability’ although he mentioned that other characteristics like seat width and window surface might also play a role. Court conceded that he related this method to utilitarianism, mentioning that in his view “Utilitarianism, seeking the good in the greatest happiness of the community as a whole, is the chief hedonistic doctrine”. He concluded that hedonic price comparisons are those which recognize the potential contribution of any commodity to the welfare and happiness of its purchasers and the community (Court 1939).

Nowadays hedonic regression models are thought to be particularly suitable to analyze product markets with extensive product differentiation and a high model turnover, in which other approaches like the matched models method fail to adequately deal with price measurement (Triplett 2004). As such, hedonic regression models are for instance commonly used in real estate appraisal or to construct price indices for consumer electronics. Considering the collector car market consists of a large number of highly differentiated models as well, an hedonic regression model thus appears perfectly suited to research the collector car market, because it provides an opportunity to create a price index for collector cars while controlling for the many product differences that exist between the various cars on offer.

1.3 Identifying the Right Characteristics for Regression

When establishing a hedonic pricing model, one of the key difficulties is the choice of characteristics (Ginsburgh & Throsby, 2006). As Ashenfelter and Graddy (2003) note, there is a strong assumption behind the use of hedonic regressions “that the set of included attributes captures almost all of the uniqueness of the products being examined”.

Unfortunately, as mentioned before, previous research on the value determinants of collector cars has been scarce. In his study, van Bergen cites Souvrain that there are five value determinants of a collector’s car (Souvrain, as cited in Orsi & Gazzi, 2008). These criteria according to Souvrain are ‘rarity’, ‘architecture’, ‘pedigree’, ‘condition’ and ‘beauty’, respectively. Souvrain however does not provide any tangible evidence to support his claims.

Because of the scarcity of previous research into the price determinants of collector cars, it might be interesting to broaden our view and look at hedonic characteristics used in some pivotal research aimed at establishing the price determinants of related items, such as regular cars or art objects of another nature and then consider whether some of those characteristics would also be applicable in the case of collector’s cars.

As mentioned under paragraph 1.1, Court (1939) started out using ‘horsepower’, ‘wheelbase’ and ‘weight’ as characteristics for his model. Griliches (1961) identified the characteristics ‘advertised brake horsepower’, ‘shipping weight’ and ‘overall length’ and added separate dummy variables to test for the influence of a car being equipped with a ‘V8’ engine, a hardtop, an automatic transmission, power steering, power brakes and a dummy variable for whether or not the car was designated as a ‘compact’. Later, Griliches extends his research to characteristics that are not directly related to the physical characteristics of the car itself by adding the characteristic ‘make’ as a proxy for qualities like prestige, reputation and service availability (Ohta & Griliches, 1976).

Studies since have used similar characteristics, but have also included characteristics of the auction itself as price determinants of used cars sold on auction (Andrews & Benzing, 2006). This study will also look into the latter, except it stands to reason that for the used car market, the characteristics of the auction that are relevant for the used car market are somewhat different than those relevant for the collector's car market. In fact, if collector's cars are to be considered 'works of art', it stands to reason that the characteristics of the auction that are relevant in determining the auction prices for art are rather than those for used cars are more useful in determining the auction prices for collector's cars. In their study about the long-term investment performance of art, Renneboog and Spaenjers found that the timing of the sale as well as the reputation of the auction house play a role in determining auction prices for art (Renneboog & Spaenjers, 2009) and therefore these variables will be included in this study as well.

2 Data and Methodology

2.1 Choice of Method

There are two main competing approaches to hedonic indexes, the hedonic imputation (HI) method and time dummy hedonic method (DTH) (Diewert, Heravi & Silver, 2007). The difference is that HI indices value a fixed period's basket of characteristics using both base period and current period hedonic coefficients and take the ratio of the latter to the former. HI index number formulas differ in their use of which period's characteristics are held constant for the valuation. DTH indices estimate price change using the coefficient on a dummy variable for time in a hedonic regression which uses both base and current period's data. For DTH indexes the slope parameters are constrained to be the same for both periods to allow the intercept shift to measure quality-adjusted price change. For HI indexes the change in the parameters over time are, paradoxically, the essence of the measure (Silver & Heravi, 2004).

There remains some debate as to which approach is best under what circumstances (Schultze & Mackie, 2002). Berndt and Rappaport (2001) and Pakes (2003) opine that when there is evidence of hedonic regression parameter instability over time, the hedonic imputation approach is preferred. This would occur for instance if consumer preferences on the characteristics of the product change over the sample period. However, benefits of the time dummy hedonic method over the hedonic imputation method include that it conserves degrees of freedom, minimizes the influence of outliers in the data and is able to give an unambiguous estimate of the measure of overall price change between periods *s* and *t* (Diewert et al., 2007). Another important benefit is that the time dummy approach is less subject to multicollinearity problems (Griliches as cited in Diewert, 2006). Griliches postulates that the justification for the time dummy method is very simple and appealing, noting that "it allows as well as possible for all of the major differences in specifications by 'holding them constant' through regression techniques. That part of the average price change which is not accounted for by any of the included specifications will be reflected in the coefficient of the time dummy and represents our best estimate of the 'unexplained-by-specification-change' average price change."

In light of the above, the time dummy hedonic method is used for this study, with prices regressed on the identified utility-bearing characteristics and on time dummies. The issue of potential parameter instability will be addressed in chapter 4. The price index (CCI) is created using the coefficients of the time dummy variables.

2.2 Functional Form

In discussing the suitability of different functional forms for hedonic regression, Triplett notes that the three most commonly used functional forms are the linear functional form, the 'double-log' function and the 'semi-log' function (Triplett, 2004). The 'double-log' function is most popular for research on computers, while the 'semi-log' function is most widely used. Muellbauer notes that the 'linear' and 'semi-log' functions are not theoretically appropriate when all buyers have identical preferences (Muellbauer, 1974). Triplett however opines that this does not reflect reality and ultimately agrees with Rosen (1974) that the choice of functional form is an empirical matter. This is consistent with Court (1939) and Otha and Griliches (1976) who both chose a semi logarithmic form for their regression because 'it provided a good fit for the data'. This study will follow suit, in this case meaning the 'semi-log' function will be used. Formally, a semi logarithmic time dummy hedonic regression can be represented as follows:

$$\ln P_{kt} = \sum_{m=1}^{M} \alpha_m X_{mkt} + \sum_{t=1}^{T} \beta_t \delta_{kt} + \varepsilon_{kt}$$

where P_{kt} represents the price of good *k* at time *t*, X_{mkt} is the value of characteristic *m* of object *k* at time *t*, δ_{kt} is a time dummy variable which takes the value 1 if good *k* is sold in period *t* and 0 if otherwise and ε_{kt} reflects the error term. The coefficients α_m reflect the attribution of a shadow price to each of the *m* characteristics, while the antilog of the coefficients β_t are used to construct a hedonic price index. Triplett notes that the antilog of the OLS regression estimate of β_t is not an unbiased estimate of the time dummy effect, but he points out that this is not problematic in the context of hedonic indices (Triplett, 2004).

2.3 Data

Concentrated data on collector car auction results are difficult to find. Auction houses often give out statements of their own results at their latest auctions and sometimes provide access to their past auction results, but this data often lacks in detail, usually only providing the make, model, model year and of course, the price. For the hedonic regression in this study however, more information on other characteristics is desired.

Ultimately, the search after data rich enough to perform a meaningful hedonic regression led to Sports Car Market (http://www.sportscarmarket.com/). Sports Car Market is a magazine about collector cars and the collector car market. They also keep a database of auction results, containing over 30.000 'detailed results' of cars sold that will be used as the primary source of data for this study. To counter bias that could exist as to what constitutes a collector's car, the assumption is made that all the cars included in Sports Car Market's database are in fact collector's cars. The database consists of five sections for every car sold, being 'basic information', 'vehicle information', 'features', 'condition description' and 'market opinion'.

In the Sports Car Market database, under 'basic information', the make, model, model year, price, auction house, auction date and the car's lot at the auction are recorded. 'Vehicle information' contains some of the physical characteristics of the cars sold such as its chassis number, engine type, displacement, induction type, reported mileage, body style, engine number, transmission type, horsepower, drive (left hand drive or right hand drive) and condition. Features includes the car's type of wheels, type of seats and the exterior and interior color. The condition description consists of the seller's account of the car's condition from '1' to '5', with the lower numbers signaling the better conditions. Finally, under 'market opinion', Sports Car Market's writers give their opinion about the car and its pricing. Although this is entertaining to read for the enthusiast and the potential buyer alike, this last category is mostly either left blank or in other cases offers such a wide array of unique information about the particular car in question that cannot be generalized or be made quantifiable. Therefore, this assessment will not be included in the regression models.

Unfortunately, although the Sports Car Market database allows a search to show 'detailed results' only, many of these 'detailed results' lack information on the characteristics mentioned above. Therefore, the choice is made to collect a sample from the database incorporating only cars for which data on 'make', 'model', 'model year', 'year sold', 'month sold', 'sale price', 'auction place', 'auction house', 'engine type', 'induction', 'displacement', 'horsepower', 'exterior color' and 'condition' are either readily available in the database or can be reliably added through secondary sources. The assumption is made that there isn't any bias in the database as to for what particular cars these data are recorded for, so that the sample remains representative of the complete database.

All the prices in the database are recorded in nominal USD. For the purpose of being able to assess the return in real terms, prices are translated into 2011 USD using the CPI index from the US Department of Labor (http://www.bls.gov/cpi/). In order to compare the Dollar returns to Euro returns, all the nominal USD prices are translated into nominal Euro prices using the daily historical spot exchange rates from either the date of the sale or the closest day recorded prior to the date of the sale. The USD/ECU, USD/EMU and finally USD/Euro spot exchange rates are used for their applicable time periods, all as recorded by the Federal Reserve (http://www.federalreserve.gov). The resulting nominal Euro prices are then translated into real 2011 Euro prices using the annual Harmonized Index of Consumer Prices (HICP) as composed by Eurostat (http://epp.eurostat.ec.europa.eu/portal/page/portal/eurostat/home/).

2.4 Choice of Variables

For hedonic regression to yield meaningful results it is crucial to identify the right variables to regress the prices on, next to year dummies, in order to control for the product differences. This study will use both physical and intangible variables to try and control for the different characteristics of the cars, and also investigate the influence of characteristics of the sale.

2.4.1 Tangible characteristics of the car

Perhaps easiest to identify are the physical characteristics of the car. These are often advertised in magazines and for some part have also been used by Court and Griliches. It seems reasonable to assume that they play a part in the value of classic cars like they do for used cars.

To check for the influence of the car's engine characteristics, the variable DISPLACEMENT will be used to check for the car's engine capacity and the variable HORSEPOWER will be used to check for the car's horsepower. These variables DISPLACEMENT and HORSEPOWER are expected to be somewhat correlated to one another yet technological advancements over time as well as the use of forced induction provide reasons to believe this correlation isn't set in stone. Dummy variables will also be used to check for the car's various engine types. The variables FOUR_CYLINDER, SIX_CYLINDER, EIGHT_CYLINDER, TWELVE_CYLINDER and OTHER_CYLINDER will account for the engine's amount of cylinders. The engine configuration included in the latter category can be found in Appendix A. The variables will equal one if the car has the corresponding amount of cylinders and zero if otherwise. Furthermore, the dummy variable FORCED_INDUCTION will be used to check whether the car has either a turbocharger, a supercharger or both and will equal one if either of those is the case and zero if otherwise.

The variable ODOMETER_KM will be used to check for one of the characteristics everyone who ever bought a used car is familiar with, namely the amount of distance it has already covered. The number will be taken over from the indicated mileage on the odometer in case it is reported and will be treated as a missing value in case it is not. For all the cars that have a reported mileage indicated in miles, the mileage figure has been transformed into kilometers in order to be able to compare all equally.

The dummy variables MY_BEFORE_1950, MY_1950_1980 and MY_AFTER_1980 will be used to check for the age of the cars and will equal one if the car in question hails from the respective time period and zero if otherwise.

The dummy variables BLACK, BLUE, GREEN, RED, SILVER, WHITE, YELLOW and OTHER_COLOR will be used to check for the one of the car's clearest characteristics for the casual observer which is the car's color. The dummies will equal one if the car has the respective color and zero if otherwise. The colors included in the OTHER_COLOR variable are included in Appendix B.

The dummy variables CONDITION#1, CONDITION#2, CONDITION#3, CONDITION#4 and CONDITION#5 will be used to check for the condition of the car and will equal one if the car has the respective condition and zero if otherwise. CONDITION#1 reflects the best possible shape a car can be in while successive conditions reflect cars that are increasingly worse off. Sports Car Market doesn't give detailed descriptions of what exactly constitutes a condition 1 car or any of the other levels but just provides the relative scale of conditions 1 through 5.

Finally, the dummy variable RACECAR will equal one if the car is described to be a racecar and the dummy variable REPLICA will equal one if the car is indicated to be a replica, meaning that it is a car not built by the original manufacturer of the model that it is supposed to replicate. Appendix F includes descriptive statistics for the tangible characteristics of the car.

2.4.2 Intangible characteristics of the car

Probably a little harder to identify and quantify are the intangible characteristics of the car that have an effect on its value. Still, even when shopping for a regular new or used car, it becomes apparent to anyone quite quickly that similar numbers on the specification sheet don't always translate in similar prices for two separate cars. Griliches and Ohta already tried to capture the intangible characteristics that they described as 'prestige' and 'reputation' in their 1976 study (Ohta & Griliches, 1976).

Sometimes it is difficult to distinguish between intangible characteristics and tangible characteristics of a car, because the two might overlap. For instance, if a car has a V12 engine, this is tangible when you look under the hood and arguably when you step on the throttle, but at the same time you might say it also gives the car a certain intangible appeal that goes beyond the mere technical aspect of having twelve pistons dancing away under the hood. An even more poignant example is perhaps the replica, a car that, when executed well, in most perceivable ways is exactly the same as the usually illustrious car it is meant to resemble, yet more often than not, is not valued accordingly.

However, in both these cases, there are still tangible characteristics one can point at to show someone what is the difference between one car and the other, and in this segment, some characteristics are suggested that capture some of those purely intangible characteristics of the car that Souvrain had in mind, like pedigree, beauty and rarity.

First, dummy variables DESIGNERS_TOP10 and DESIGNERS_VOTES will be included to check if the cars that are considered to be among the most beautiful by a group of the world's most renowned car designers require a premium. The separate dummy variables are for cars that respectively made the Top 10 and cars that at least received votes in a onetime 2009 survey by Classic and Sports Car Magazine among 20 of the world's best car designers (http://www.thetruthaboutcars.com/2009/02/car-designers-citroen-ds-most-beautiful-car-in-the-history-of-the-world-ever/). Appendix E contains an overview of the respective designers and the cars they chose. As this survey hasn't been repeated since, this study assumes that the car designer's tastes have stayed the same in the meantime and that they thus consider the cars they found the most beautiful in 2009 still the most beautiful today.

Then, dummy variables for separate brands will be included to look at their individual impact on the auction prices. The dummies that will be included are for FERRARI, ASTON_MARTIN,

CHEVROLET, FORD, JAGUAR, MERCEDES, PORSCHE and OTHER_BRAND respectively. The manufacturers included in the latter variable are displayed in Appendix C.

Finally, the dummy variable BRAND_EXTINCTATSALE will be used to indicate if the car sold belonged to a brand that was extinct at the time of the sale at the auction. Appendix G includes descriptive statistics on the intangible characteristics of the car.

2.4.3 Characteristics of the sale

Finally, dummies are included to check for the effects of the timing and location of the sale, as well as the name of the auction house.

Month dummies are included to indicate the month in which the sale took place. Auction house dummies for BARRET_JACKSON, BONHAMS, BROOKS, KRUSE, CHRISTIES, McCORMICK, MECUM_AUCTIONS, RM_AUCTIONS, EBAY and OTHER_AUCTIONHOUSE will indicate the auction house that took care of the sale and the dummy variables. Auction houses included in the latter variable are included in Appendix D, while descriptive statistics on the abovementioned variables are included in Appendix H.

3 Empirical Results

3.1 Model choices explained

This chapter outlines the results of different hedonic regression models on the pooled data. In all cases, the model is estimated using OLS and the dependent variable for this chapter is always the natural log of the real sale price in US Dollars. Model (1) only includes time dummies, while regression model (2) adds the tangible characteristic of the car. The third model (3) then adds the intangible characteristics of the car to the regression analysis and the fourth model (4) is the main model and includes all the independent variables, including those for the characteristics of the sale. Appendix I provides an overview of the variables included in the respective models.

In each case with dummy variables one category is left out of the regression to prevent the dummy variable trap of perfect multicollinearity. Appendix I also provides an overview of the estimated models' respective Adjusted R^2-values, showing that the models explain 1.2%, 53.8%, 59.9% and 63.7% of the natural log of the real US Dollar collector car prices' variance, respectively.

3.2 Coefficients discussed

3.2.1 Tangible characteristics of the car

As was to be expected, the explanatory power of model (1) with only the time dummies added as independent variables is very low. By adding the variables for the tangible characteristics to model (1) in order to create model (2), the explanatory power jumps from a measly 1.2% to 53.8% meaning at least few of the variables that were suspected to have an influence on collector car prices, are indeed guilty of said influence.

The variables SIX_CYLINDER, TWELVE_CYLINDER and FORCED_INDUCTION that describe the technical attributes of the car's engine show fairly strong and statistically significant effects on collector car prices. As the variable EIGHT_CYLINDER is left out in this case to prevent the dummy variable trap, it is interesting to note that the variable SIX_CYLINDER has a positive sign. It might be explained though through the abundance of eight cylinder engines in the American muscle cars included in the sample that are typically less costly than some of the European exotics with six cylinder engines. Interestingly, the variables ODOMETER_KM as well as HORSEPOWER show an influence on the dependent variable that while statistically significant, is almost negligible in size. The variable DISPLACEMENT was ultimately left out of the model as its inclusion did cause problematic multicollinearity issues.

As for the age of the car, the variables MY_BEFORE_1950 and MY_1950_1980 show a very strong positive influence on the dependent variable compared to the MY_AFTER_1980 variable that was left out. This might be explained as a survivorship issue as older cars have literally had to survive and prove their value over at least a couple of decades to still be on the market today, while for new cars it remains to be seen which ones will be considered valuable in the future.

Almost all the condition variables have the expected signs and also show a great influence on car prices, with the exception of the CONDITION#5 variable which shows very slightly positive, albeit not statistically significant, compared to the CONDITION#4 variable that is left out. This is most likely explained because there are very few observations in the sample of CONDITION#5 cars. The variables CONDITION#1 and CONDITION#2 show particularly strong positive effects, as does the RACE_CAR variable, indicating race cars are valued higher than their road going counterparts. The Replica variable shows a relatively small positive effect. This may seem counter intuitive, but can be explained because replicas are usually only made to replicate the most renowned cars and can have excellent build quality, so while not as expensive as their original 'siblings', they can still be valued higher than the average collector car on auction. Finally, none of the color variables show a statistically significant relationship with the dependent variable compared to the BLACK variable which is left out.

3.2.2 Intangible characteristics of the car

After adding the variables for the intangible characteristics of the car to create model (3), the Adjusted R^2-values increases a little more in comparison to model (2) to 59.9%, even though the incremental gains are necessarily smaller.

All the tangible characteristics shown to have statistically significantly relationships with the price of collector cars in model (2) also do so in models (3).

As far as the intangible variables go, the variable DESIGNERS_VOTES is highly significant and has a strong positive influence on the dependent variable. In comparison to the left out variable MERCEDES, the variable FERRARI has a positive sign yet is not statistically significant, the variables ASTON_MARTIN and PORSCHE have small negative signs but are also not statistically significant, while the variables FORD, CHEVROLET, JAGUAR and OTHER_BRAND all have quite substantial and statistically significant negative signs. This indicates that the Mercedes in the sample are valued quite highly compared to Fords, Chevrolets and Jaguars in particular. The lower valuations for Fords and Jaguar might go some way of explaining the positive sign of the SIX_CYLINDER variable compared to the EIGHT_CYLINDER variable found in the previous section as eight cylinder engines can often be found under the bonnet of cars from these two brands. The negative sign for Jaguar might be more surprising, especially because some Jaguars are included in DESIGNERS_VOTES variable which has a strong positive sign. This could indicate that some Jaguar models are valued particularly strong, while others are not.

The final intangible characteristic variable BRAND_EXTINCTATSALE shows a small negative sign, indicating that cars from extinct brands might be valued lower than cars from active brands, however this result is not statistically significant.

3.2.3 Characteristics of the sale

To create the main model (4) from model (3), the variables that describe the characteristics of the sale are added to model (3). The Adjusted R^2-values increases a little more yet in comparison to model (3) to 63.7%, Compared to model (3) this does not have a big influence on the aforementioned variables described in the previous sections with the exception of two variables, CONDITION#5 and ASTON_MARTIN respectively that have changed signs. CONDITION#5 now shows the expected negative sign while ASTON_MARTIN now shows a small positive sign. Both of these variables remain statistically insignificant though which probably explains the change.

As the auction house variable McCORMICK is left out, all the other auction house variables BARRET_JACKSON, BONHAMS, BROOKS, KRUSE, CHRISTIES, MECUM_AUCTIONS, RM_AUCTIONS, EBAY as well as OTHER_AUCTIONHOUSE are all positive and statistically significant. This is likely due to McCormick focusing more on the lower end of the market. Compared with each other, the auction houses Christie's, Barret-Jackson and RM Auctions have the biggest positive signs, indicating they have the biggest impact on the sale price. However, Renneboog and Spaenjers (2009) remark that the relationship between the auction house's reputation and the price of a particular art piece auctioned by one of these auction houses may simply be one of correlation rather than causality. It cannot be ruled out that this positive correlation is due to big name auction houses generally auctioning off higher quality art pieces than the average auction house. It stands to reason that this may not only be the case for art but also for collector cars. However, some crosstabs analysis included in Appendix J suggest that it might yet be the auction houses themselves adding value.

Finally, there are a few month dummies that show statistically significant relationships with the dependent variable, namely APRIL, AUGUST and SEPTEMBER. APRIL and AUGUST are significant and negative and the month dummy AUGUST is significant and positive. The latter may be partly explained by the influence of high profile auctions that traditionally take place in August and are sometimes regarded as the start of the 'auction season', like the ones conducted in the festivities around the Pebble Beach Concours d'Elegance which takes place in August every year in California. Possibly then, the negative sign of September is because August's buyers are cutting expenses after August's expenditures.

Appendix K shows the parameter estimates of the hedonic variables for model (4). To show the economic significance of each of the variables, Appendix K also includes the "Price Impact" of each hedonic variable, which can be calculated by taking the exponent of the coefficient and subtracting one (Thornton & Innes, 1989). However, once again it is important to note that in some cases the regression coefficients may reflect correlation instead of causality.

3.3 Price Index, conveniently coined CCI

After establishing the coefficients on all the other variables, this study aims to construct a price index for collector cars based on the coefficients of the year dummies. As explained in section 2.1 and in similar fashion to the "Price Impact" calculations on the other variables, the price index will be constructed by taking the exponent of the coefficient of the respective year dummies and subtracting one to calculate the "Price Impact" for each of the years from 1997 through 2011, while the price level in 1996 is standardized to 100. All the results are in real terms unless otherwise specified (as a robustness check in the next chapter the model will also be regressed on the nominal sale prices).

Appendix L shows the price index for model (4). The model shows a geometric mean real return of 13.52% and a substantial volatility of 34.45%. This might indicate that the collector car market is subject to a boom and bust phases. There are some years where the index is relatively steady, however it is subject to occasional spikes. the geometric mean real return calculated for the period between 2000 and 2004 for instance is a much lower 2% with a volatility of a comparably low 10.71%. It must be noted however that not all the year dummies are proven to be statistically significant. Therefore these results are not proven beyond statistical doubt and the next chapter will try to investigate some of the potential issues and pursue some additional information.

4. Robustness checks and extensions

This chapter will put some more hurdles in the way of the model put forth in chapter 3 to check how it stands up. First, the potential issues of outliers in the dependent variable is discussed. Second, regression results of the adjacent period model will be compared to the results in chapter 3 in order to address the issue of potential parameter instability as a consequence of changing tastes. Third, the natural log of nominal dollar prices as well as the natural log of real 2011 Euro prices will be used as the dependent variable to see if and if so how it affects the coefficients on the time dummies. And finally, there will be investigated whether or not there is a masterpiece effect.

4.1 The issue of potential outliers

While chapter two mentions that Diewert et al. (2007) note that one of the benefits of the hedonic time dummy approach is its minimizing effect on outliers, Diewert simultaneously answers his own question about the suitability of the deletion of outliers in the hedonic regression context with the notion that in the unweighted context, the deletion of sample outlier observations should be permitted (Diewert, 2003). He then goes on to say that since influence analysis is just an extension of outlier analysis (an influential observation is one which greatly influences the estimated regression coefficients), hence the deletion of influential observations should also be permitted.

To evaluate the impact of outliers on model (3) the same regression is performed except for the fact that the data on LN_REAL2011$PRICE is winsorized before regression analysis. This means data entries will not be deleted from the sample but instead, extreme values are set to maximum and minimum boundaries. The maximum and minimum values are derived from Tukey's Hinges, resulting in 18 changes from LN_REAL2011$PRICE to LN_REAL11$WINSOR. As a result of this procedure the Adjusted R^2 increases marginally from 63.7% to 64.1%. It doesn't change the model dramatically in terms of statistical significance nor in measure of effect of the independent variables on LN_REAL11$WINSOR. Appendix M shows the coefficients on the year dummies do change slightly though and the resulting numbers are a geometric mean real return of 12.68% with a volatility of 33.33%, but the numbers remain similar to those for model (4).

4.3 The issue of parameter instability

As mentioned in chapter two, a potential problem with the hedonic time dummy approach is that the coefficients are constrained to be stable across the whole sample window. This is a strong assumption as peoples' tastes may change over time. Triplett argues that the "adjacent period approach" is a good alternative methodology as it does not pool the data over all periods, but considers two adjacent periods at a time (Triplett, 2004). The hedonic coefficients are only fixed over short time frames. Therefore, the resulting price index theoretically not only controls for changes in quality, but also for fluctuations in the shadow prices of each characteristic measuring this quality. We apply the adjacent period regression approach to our dataset by performing a separate hedonic regression for each period of two adjacent years. For example, data is pooled for 2010 and 2011 and a year dummy is included for 2011. Then data is pooled for 2009 and 2010, and so forth.

Unfortunately it quickly becomes quite clear that all except for two of the year dummy regression coefficients in the pooled data of just two years are not statistically significant. Most likely the relatively small pooled data samples created by this approach cause too much of the variance in the dependent variable to be ascribed to the year dummies, resulting in a very high 73.96% geometric mean real return estimate with 166.28% volatility, as can be seen in Appendix N. A lot of both that return and the volatility however can be explained by the value for 1998. In fact if one were to take the period 1999-2010, the results would come down to a reasonable 12.77% return and 26.78% volatility.

4.4 Different appearance of the dependent variable

In this section, the dependent variable LN_REAL2011$PRICE is replaced by two different variants, namely LN_REAL2011EUROPRICE and the natural log of the nominal sales price in US Dollars, LN_NOMINAL$PRICE, respectively. To be able to compare results, results on the latter will be discounted for inflation after the regression analysis, using the CPI index statistics from the US Department of Labor mentioned in chapter 3.

After replacing LN_REAL2011$PRICE with LN_ REAL2011EUROPRICE, the Adjusted R^2 value rises marginally from 63.7% to 64.1%. All the signs, magnitudes and significances of the regression coefficients are very similar to the original model (4).

It's much the same story after replacing LN_REAL2011$PRICE with LN_NOMINAL$PRICE. The Adjusted R^2 value rises to 63.8% compared to the original model (4), all the coefficients are very similar, which shows that the model (4) is not too sensitive against changes in the specification of the model. Implied price indices for these two adaptations of model (4) are to be found in Appendix O and Appendix P respectively.

4.5 Investigating the masterpiece effect

In their study on prices and returns in the art market, Renneboog and Spaenjers found that the highest quality art pieces, 'superstar art', performed better in the marketplace than the average art object (Renneboog & Spaenjers, 2009). There is a clear rationale for this phenomenon, known as the masterpiece effect, that ultimately boils down to the simple rules of supply and demand. In the world today there are ever more people that have the means, alongside the passion, to acquire the top pieces. However, the supply of real top pieces remains fairly constant, especially for some categories of art.

The latter also seems to apply to the top of the top of the collector car market, the supply of the most coveted models is fixed since they're just not being built anymore, while the demand is on the rise from new markets all over the world. This seems like a logical explanation as to what is the driving force behind the new records being broken on a seemingly fairly regular basis at auctions these days.

Earlier regressions have already shown that the variable DESIGNER_VOTES has a highly positive, highly significant relationship with the price of cars in the regression models, which may indicate something in the direction of a masterpiece effect. To test this idea, regression with all relevant variables of model (3) is executed once again, except this time only for cases for which the dummy variables DESIGNER_VOTES equal 1. This way, all the other cars that do not meet this requirement will be neglected for this particular regression, so that it can be checked if particular rules apply for masterpieces as defined by well-known car designers.

In both cases the regression results in healthy R^2 values and extremely high values of the year dummies but unfortunately, the latter are not statistically significant and not estimated for every year. Unfortunately, there seems to be too much variance that can't be adequately assigned to the separate variables in the model, so no definitive conclusions can be drawn on this particular topic. One thing that's interesting to note however is that the sale price of cars included in the category DESIGNER_VOTES seems to be extremely sensitive to the CONDITION#1 and CONDITION#2 variables, much more so than the cars in the general model. This may yet be another thing to point in the direction of a masterpiece effect since it seems to indicate that the most beautiful cars in the best condition require a hefty premium.

5. Comparison with other financial assets

After the robustness checks conducted in chapter 4, it is time to compare the model to other financial assets and ponder whether collector cars in fact have a role to play as a viable investment object. This chapter will examine how the Collector Cars Index created in chapter 3 stacks up against and correlates with more traditional assets.

5.1 Other indices at a glance

Of course after creating a price index for collector cars, the next logical step is to compare it with other asset classes. In this section, the CCI will be compared to returns on T-bills, 10 year U.S government bonds, The MSCI US, European, UK as well as the MSCI World Index, the S&P GSCI Commodity Spot - PRICE INDEX, the S&P GSCI Four Energy Commodities Spot - PRICE INDEX and the MSCI EUROPE REAL ESTATE $ - PRICE INDEX. To be able to compare all equally and to avoid problems with outliers with the covariance analysis Log returns are calculated for all these assets. Appendix Q shows the Log of mean results and the respective volatility of all the aforementioned assets as well as their Sharpe ratios. At first sight the CCI stacks up quite well against the other indices as only the 10 year U.S bonds and commodity indices have higher Sharpe ratios.

Next it is useful to look at the correlations between the CCI and the other indices. Even if the CCI does not give the very best returns on investment at first sight, it could still be very a very useful asset to investors who may be able to diversify their investment portfolios with different assets compared to what they usually invest in. As it turn out however and in contrast to findings by van Bergen (2009), the CCI shows a negative correlation with the bond indices and the commodity indices and positive correlation with the stock indices and European real estate market. None of the correlation coefficients are very big though, so it’s necessary to look a little further still. Appendix R shows the correlation matrix between the different assets.

5.2 Hypothetical portfolios

To conclude this chapter a couple of hypothetical investment portfolios are considered to see if collector cars deserve a natural place in such a portfolio. In order to create said portfolios, first a covariance matrix is constructed based on the log return of the various investment assets and then the 'solver' function is used in Microsoft Excel to calculate and maximize the expected returns, volatilities and Sharpe ratios of the portfolios.

As the benchmark specification, all the assets are represented with a 10 percent stake in the portfolio, which results in a μ of 2.5% with 5.2% volatility and a Sharp value of .19 for the portfolio. Second, the 'solver' function is called upon to maximize the return while at the same time only allowing for the portfolio to have the volatility of the least volatile single investment asset, the US government bonds. The result of this is a μ of 2.0% with a standard deviation of 0.4%, so it's indeed just a little bit higher than the 1.9% one can get on the individual asset with the same standard deviation. The perhaps more interesting thing for this study however is that in this model where the weights of the relative assets in the portfolio are left over to be optimized by the software, the model proposes a small investment in collector cars next only to a small percentage of energy commodities and a big portion of US government bonds.

The intention of the next specification was to purely try and minimize the portfolio volatility. Unfortunately however it worked out so well that it worked out too well, as the model thinks that through a strategy of buying long term bonds and short term T-bills one can get a small positive return without any risk at all, but as that would create an opportunity for arbitrage this has to be written off as an imperfection somewhere in the data.

In the final specification, a constraint was added to the model that the portfolio should consist for at least 10% of investments in classic cars in order to examine what other assets would be added to the model in that case to complement the portfolio. In line with what already could be seen in specification 2. An overview of the different specifications can be found in Appendix S.

6. Conclusions and Discussion

The aim of this study was threefold. The first intention was to establish and investigate factors that determine collector car prices at auctions, the second was to try and construct a price index of the collector car market and the ultimate goal was to establish if collector cars are in fact a viable investment object to be included in financial portfolios or if they should simply remain in the realm of the enthusiast going to the odd track day, classic rally, or maybe leisurely Sunday drive on a sunny day. In order to achieve these goals, a dataset with auction data was constructed compromising of 1,200 cars sold on auction between 1996 and 2011.

6.1 Conclusions

As for the first aim, the study identified some clear characteristics of the cars themselves as well as characteristics of the sale that play an important role in the eventual sale price. These characteristics have been divided in tangible characteristics of the car, intangible characteristics of the car and characteristics of the sale.

Concerning tangible characteristics of the car, this study found the most important factors driving the sale price to be a good condition of the car, the age of the car, with older cars being valued more highly, the car being equipped with a V12 engine and finally the car being classified as a race car. Other tangible characteristics of the car like the color of the paint did not prove to have a statistically significant effect on the sale price while the amount of horsepower turned out to have almost no influence on sale prices at auction.

For the intangible characteristics of the car the beauty of the car as captured by the variable DESIGNER_VOTES proved to be the most important determinant of a high auction price. As the dummy variable MERCEDES was left out of the model to set the benchmark, it was shown that in comparison to Mercedes, some of the other brand names, namely Ford, Chevrolet and Jaguar, had a negative impact on the auction price. Ferrari and Aston Martin did show slightly positive signs however not statistically significant ones and nor did the variable BRAND_EXTINCT_AT_SALE, meaning that whether a car brand has folded or still selling cars today has no significant influence on a car's auction price.

Finally in terms of the characteristics of the sale, perhaps the most interesting find was that August is the only month that statistically significantly generates higher auction prices at auctions compared to the other months, while September is one of two months (along with April) that is proven to be a slow months for car auction values. This study proposes that the high auction results in August can be explained by the yearly high profile car auctions traditionally held in August and that the dip in September is a result of everyone focusing their attention on these world renowned auction events. It was also shown that some Auction houses yield higher auction sale prices than others, with Christie's, RM Auctions and Barret-Jackson being the ones who manage to sell at the highest prices. A school of thought is that this is a matter of correlation instead of causality, however this study found some evidence that these three particular auction houses do not necessarily sell a higher percentage of cars with value adding characteristics above compared to their fellow auction houses, indicating that the reputation of the auction houses itself may well be value adding. This issue is something that could be further investigated in future research.

With the price determinants determined, this study then went on to aim two which was to create a price index for collector cars (CCI) using the time dummy hedonic regression method. Over the 1996-2011 time period, the resulting index yielded an average annual return of 13.52% with a volatility of 34.45%.

These figures on returns and volatility were then compared with other asset classes, including 3-month US T-bills, 10 year U.S government bonds, the MSCI US Index, MSCI European Index, MSCI UK Index as well as the MSCI World Index, the S&P GSCI Commodity Spot - PRICE INDEX, the S&P GSCI Four Energy Commodities Spot - PRICE INDEX and finally the MSCI EUROPE REAL ESTATE $ - PRICE INDEX. It turned out that the CCI Index had the fourth best Sharpe ratio in this diverse group of financial assets, comparable to both the commodity indexes, while at the same it showed that the CCI has a negative correlation with the bond indices and the commodity indices and positive correlation with the stock indices and European real estate market.

With the latter in mind, this study finally tried to fulfill the final aim of this study to look at the potential role of collector cars in investment portfolios. In order to do so, four hypothetical portfolios were constructed by calculating annual log returns for all the assets mentioned above, creating the covariance matrix for these assets and then using the 'solver' tool in Microsoft Excel to calculate the optimal weights of the various assets within the respective portfolios limited by different constraints. The results showed that under certain circumstances, a small investment in collector cars did add value to the portfolio.

6.2 Discussion and limitations

This study concludes that collector cars can provide a viable investment opportunity. However, there are some limitations to this study. For instance, there are a few practical issues with investing in collector cars that are left out of this study.

First of all, there is the issue of transaction costs that is not considered in this study, even though it's a safe assumption that transaction costs on collector cars are significantly higher than those on traditional assets like stocks, bonds and a wide array of all kinds of financial derivatives.

Second, other than transaction costs there are other costs one could take into account that are the drawbacks of owning an asset that is rather sizeable in the literal sense compared to a balance somewhere on a piece of paper. There are for instance the maintenance costs, the storage costs and the insurance costs to worry about. But then of course in theory the asset does also provide an opportunity to generate value if one wouldn't mind renting it out. In the interest of not complicating things more than necessary these issues are left beyond the scope of this study.

A recommendation for future research is the creation of a database with qualitative data on auction results. For this study it proved to be quite difficult and time consuming to obtain the qualitative data on all the various characteristics of the respective collector cars that are necessary to perform the hedonic regression analysis which seems ideally suited to the collector car market due to the heterogeneity within the 'collector car group'. A vast database with complete data on cars sold on auction would be a tremendous help for future research in this field.

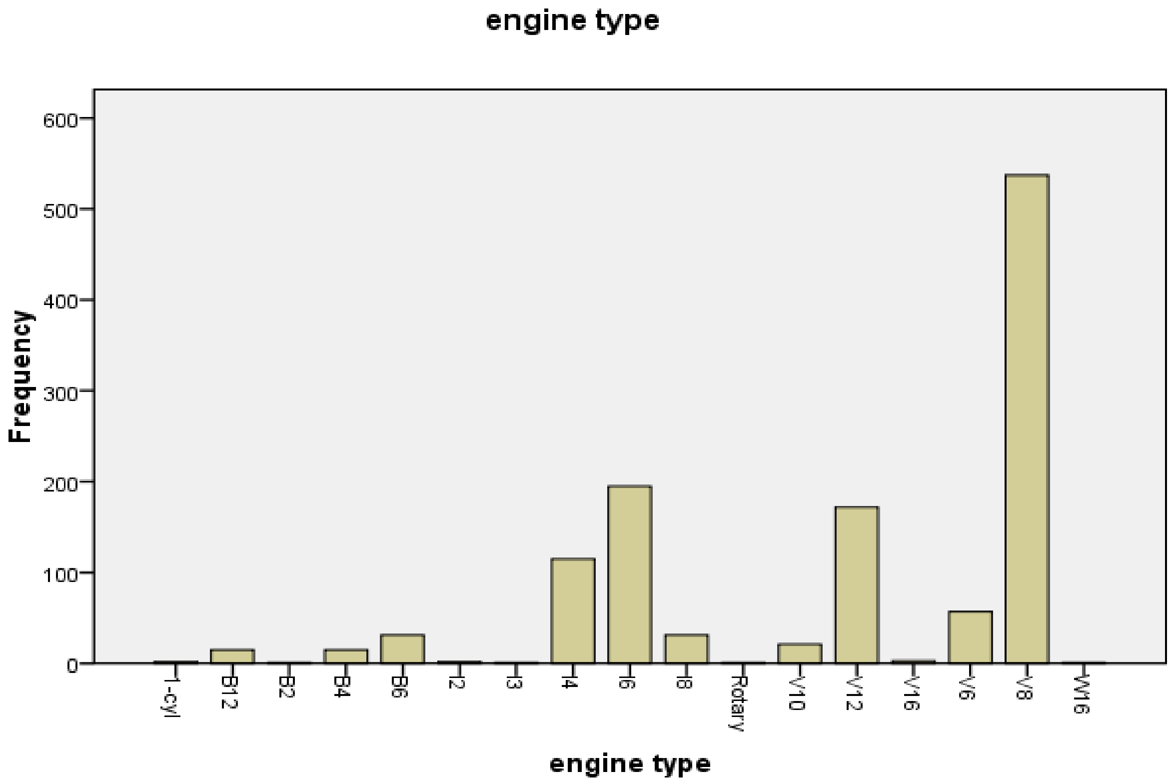
To finish off, the author of this study recommends that all the owners of collector cars don't worry but rather enjoy the benefits of owning this physical asset and don't let them gather dust in a shed. And partly in light of the results of this study there's one quote from an otherwise rather mediocre old movie uttered at the behest of a Ferrari 250 GT SWB California Spyder that seems quite suitable here as a final sentiment for collector cars in general:

"If you have the means…..I highly recommend picking one up"

Appendices

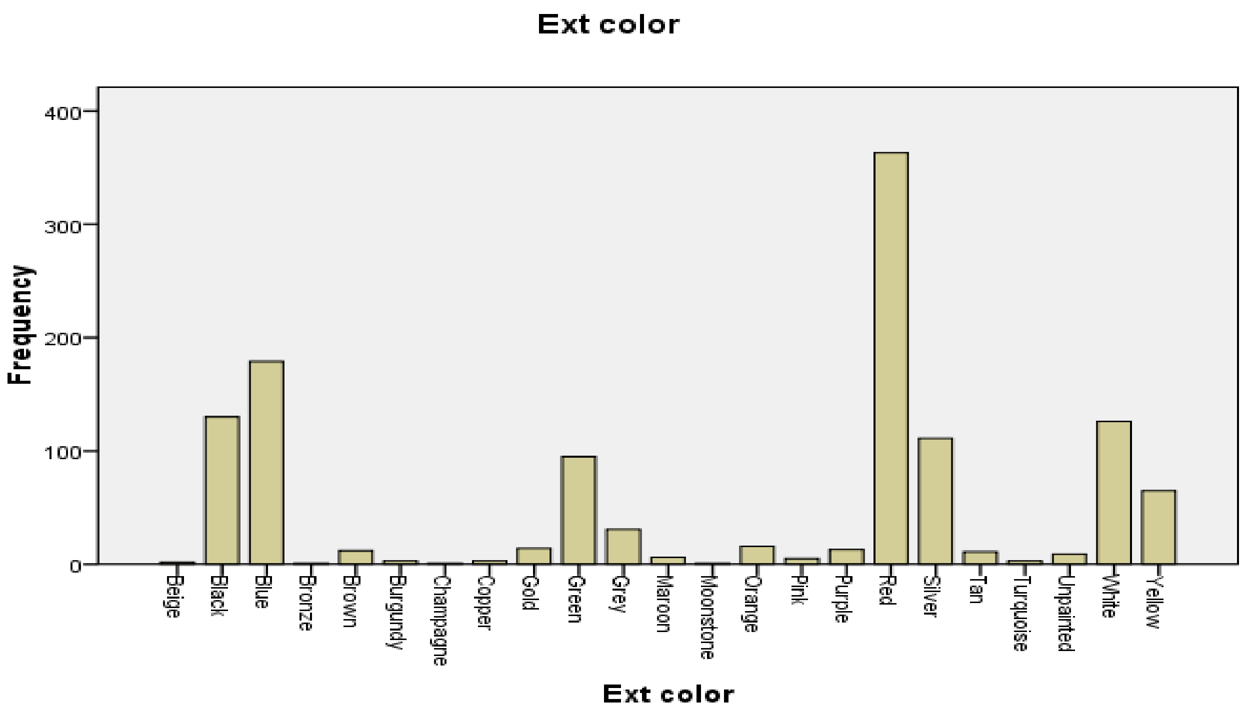
Appendix A – Engine types included under OTHER_CYLINDER

Apart from the four cylinder, six cylinder, eight cylinder and twelve cylinder engines the sample contains the following engine types that are captured by the variable OTHER_CYLINDER: 1-cyl, 2 cylinder boxer engine (B2), inline-2 cylinder engine (I2), inline-3 cylinder engine (I3), Rotary engine, 10 cylinder engine (V10) and sixteen cylinder engine (V16 or W16). Below the frequencies are depicted in a graph.



Appendix B – Colors included under OTHER_COLOR

Apart from the colors BLACK, BLUE, GREEN, RED, SILVER, WHITE and YELLOW the sample contains the following other colors that are captured by the variable OTHER_COLOR: Beige, Bronze, Burgundy, Champagne, Copper, Gold, Grey, Maroon, Moonstone, Orange, Pink, Purple, Tan, Turquoise and unpainted. The graph below depicts somewhat ironically depicts all the colors in the sample



Appendix C – Brands included under OTHER_BRAND

Apart from the brands FERRARI, ASTON_MARTIN, CHEVROLET, FORD, JAGUAR, MERCEDES and PORSCHE the sample contains the following other brands that are captured by the variable OTHER_BRAND: AC, Acura, Alfa Romeo, Alpine, Alvis, AMC, American, American Bantam, Arnolt-Bristol, Arrows, Auburn, Austin, Austin-Healey, Batmobile, Bentley, Blastolene, BMW, Bugatti, Buick, Cadillac, Callaway, Caterham, Chrysler, Citroën, Clenet, Datsun, De Tomaso, Delage, Delahaye, DeLorean, DeSoto, De Tomaso, Dodge, Duesenberg, DuPont, Edsel, Facel Vega, FIAT, Germain, Ghia, Ginetta, GMC, Hispano-Suiza, Hupmobile, Invicta, ISO, Jensen, Kurtis Kraft, Lagonda, Lamborghini, Lanchester, Lancia, Land Rover, Lexus, Lincoln, Lola, Lotus, Maserati, Mazda, McLaren, Mercury, MG, Mini, Modena, Morgan, Napier, Nash, Noble, Oldsmobile, Packard, Panoz, Peugeot, Pierce-Arrow, Plymouth, Pontiac, Prost-Peugeot, Railton, Renault, Riley, Rolls Royce, Rover, Saleen, Shelby, Smart, SSC, Studebaker, Stutz, Subaru, Sunbeam, Talbo, Talbot-Lago, Toyota, Triumph, Tucker, TVR, Ultima, Vector, Volkswagen, Volvo and Willys.

Appendix D – Auction Houses included in the sample

Apart from the auction houses BARRET_JACKSON, BONHAMS, BROOKS, KRUSE, CHRISTIES, McCORMICK, MECUM_AUCTIONS, RM_AUCTIONS and EBAY other auction houses included in the sample and captured in the variable OTHER_AUCTIONHOUSE are: Artcurial-Briest-Poulain Le Fur, Barons, Coys, H&H Auctions, Sotheby’s and Sportscar, Auctions America by RM, Aumann Auctions, Autoclassic, B-J/Coys, Branson, Carlisle Events, Carriage House, Cole, Gooding & Co., Hershey Auction LLC, Hollywood Wheels, James Murphy, Keenan Auction Company, Kensington, MidAmerica, Motley Auctions & Realty Group, Potts Auction Company, Premiere, Russo and Steele, Silver Auctions, Spectrum, The Auction Inc, The Worldwide Group, VanDerBrink Auctions, Wayne Pike Auctions, Worldwide Auctioneers.

Appendix E – Most beautiful cars in the history of the world as judged by well-known car designers

To capture the subjective, intangible characteristic of the beauty of a car, this study uses two variables, DESIGNERS_TOP10 and DESIGNERS_VOTES that include cars deemed the most beautiful by a jury of 20 renowned car designers. The jury consisted of Dennis Adams, Roy Axe, Paul Bracq, Ian Callum, Russel Carr, Steve Crijns, Leonardo Fioravanti, Marcello Gandini, Giorgetto Giugiaro, John Heffernan, Tom Karen, Patrick le Quément, Paulo Martin, Gordon Murray, Ken Okuyama, Martin Smith, Peter Stevens, Julian Thomson, Tom Tjaarda and Oliver Winterbottom.

The models included in the DESIGNERS_TOP10 category are the Citroën DS, Jaguar XK120, Ferrari 275 GTB, Cord 810/812, Ferrari 250 GT Lusso, Ferrari 250 GT SWB, Jaguar E-type, Lamborghini Miura, Lotus Elan and Lotus Elite ('57).

Models included in the DESIGNERS_VOTES category include all the models from the DESIGNERS_TOP10 as well as the Alfa Romeo Canguro, Aston Martin DB9, Audi A6, Bentley Continental GT, Bentley R-Type Continental, Bertone BAT 5, Bertone Marzal, BMW 328 Mille Miglia, Bugatti T41 Royale Coupé Napoleon, Bugatti T57SC Atlantic, Buick Riviera (1963-'65), "Cadzilla", Citroën ID/DS, Cord 810/812, Delage D8-120S, Ferrari 166 Barchetta, Ferrari 250 GT Lusso, Ferrari 250 GT SWB, Ferrari 250 GTO, Ferrari 275GTB, Ferrari 330 P3/4. Ferrari Dino 206 S, Ferrari Dino 246 GT, Ferrari P6, Ford GT40, Hispano-Suiza H6 (Tulip Wood), Jaguar E-type, Jaguar XJ6 S1, Jaguar XK120, Jaguar XKSS, Lagonda Rapide, Lamborghini Countach, Lamborghini Gallardo, Lamborghini Miura, Lancia Stratos, Lincoln Continental (1961), Lotus Elan +2, Lotus Elan S3, Lotus Elite (1957), Maserati Boomerang, Maserati Khamsin, Mercedes-Benz 500K, Mercedes-Benz Gullwing 300SL, Mini, Pagaso Z102 'Thrill', Phantom Corsair and the Triumph TR4

Appendix F – Descriptive statistics; tangible characteristics of the car

Variables, Number of valid observations, minimum observation, maximum observation, mean and standard deviation. Percentiles included below. If the mean of a dummy variable with value '0' or '1' is X, that means for X percent of the cases the dummy variable is 1.

Kolom1		Descriptive Statistics				
	N	Minimum	Maximum	Sum	Mean	Std. Deviation
DISPLACEMENT	1200	0	13	4785.8	3.988	1.6788
HORSEPOWER	1199	8	920	342785	285.89	146.716
Condition	1200	1	5	2758	2.3	0.86
FOUR_CYLINDER	1200	0	1	130	0.11	0.311
SIX_CYLINDER	1200	0	1	283	0.24	0.425
EIGHT_CYLINDER	1200	0	1	568	0.47	0.499
TWELVE_CYLINDER	1200	0	1	187	0.16	0.363
OTHER_CYLINDER	1200	0	1	32	0.03	0.161
FORCED_INDUCTION	1200	0	1	126	0.11	0.307
ODOMETER_KM	837	0	308480	39909798	47681.96	47694.58
MY_BEFORE_1950	1200	0	1	111	0.09	0.29
MY_1950_1980	1200	0	1	590	0.49	0.5
MY_AFTER_1980	1200	0	1	499	0.42	0.493
BLACK	1200	0	1	130	0.11	0.311
BLUE	1200	0	1	179	0.15	0.356
GREEN	1200	0	1	95	0.08	0.27
RED	1200	0	1	363	0.3	0.46
SILVER	1200	0	1	111	0.09	0.29
WHITE	1200	0	1	126	0.11	0.307
YELLOW	1200	0	1	65	0.05	0.226
OTHER_COLOR	1200	0	1	131	0.11	0.312
CONDITION#1	1200	0	1	229	0.19	0.393
CONDITION#2	1200	0	1	468	0.39	0.488
CONDITION#3	1200	0	1	424	0.35	0.478
CONDITION#4	1200	0	1	74	0.06	0.241
CONDITION#5	1200	0	1	5	0	0.064
RACE_CAR	1200	0	1	38	0.03	0.175
REPLICA	1200	0	1	15	0.01	0.111
Valid N (listwise)	836					

		Percentiles						
		5	10	25	50	75	90	95
Weighted Average(Definition 1)	DISPLACEMENT	1	2	3	4	5	6	7
	HORSEPOWER	85	120	205	300	380	476.6	550
	Condition	1	1	2	2	3	3	4
	FOUR_CYLINDER	0	0	0	0	0	0	1
	SIX_CYLINDER	0	0	0	0	0	1	1
	EIGHT_CYLINDER	0	0	0	1	1	1	1
	TWELVE_CYLINDER	0	0	0	0	0	1	1
	ODOMETER_KM	195.4	800	7696.5	33336	75866.75	117159	140802.1
	MY_BEFORE_1950	0	0	0	0	0	0	1
	MY_1950_1980	0	0	0	0	1	1	1
	MY_AFTER_1980	0	0	0	1	1	1	1
	BLACK	0	0	0	0	0	1	1
	BLUE	0	0	0	0	0	1	1
	GREEN	0	0	0	0	0	0	1
	RED	0	0	0	0	1	1	1
	SILVER	0	0	0	0	0	0	1
	WHITE	0	0	0	0	0	1	1
	YELLOW	0	0	0	0	0	0	1
	OTHER_COLOR	0	0	0	0	0	1	1
	CONDITION#1	0	0	0	0	0	1	1
	CONDITION#2	0	0	0	0	1	1	1
	CONDITION#3	0	0	0	0	1	1	1
	CONDITION#4	0	0	0	0	0	0	1
	CONDITION#5	0	0	0	0	0	0	0
	RACE_CAR	0	0	0	0	0	0	0
	REPLICA	0	0	0	0	0	0	0

Appendix G – Descriptive statistics; intangible characteristics of the car

Variables, Number of valid observations, minimum observation, maximum observation, mean and standard deviation. Percentiles included below. If the mean of a dummy variable with value ‘0’ or ‘1’ is X, that means for X percent of the cases the dummy variable is 1.

Descriptive Statistics

	N	Minimum	Maximum	Sum	Mean	Std. Deviation
DESIGNERS_TOP10	1200	0	1	45	0.04	0.19
DESIGNERS_VOTES	1200	0	1	72	0.06	0.238
FERRARI	1200	0	1	185	0.15	0.361
ASTON_MARTIN	1200	0	1	62	0.05	0.221
CHEVROLET	1200	0	1	194	0.16	0.368
FORD	1200	0	1	70	0.06	0.234
JAGUAR	1200	0	1	71	0.06	0.236
MERCEDES	1200	0	1	96	0.08	0.271
PORSCHE	1200	0	1	45	0.04	0.19
OTHER_BRAND	1200	0	1	477	0.4	0.49
BRAND_EXTINCTATSALE	1200	0	1	100	0.08	0.277
Valid N (listwise)	1200					

Percentiles

		Percentiles					
		5	10	25	50	75	90
Weighted Average(Definition 1)	DESIGNERS_TOP10	0	0	0	0	0	0
	DESIGNERS_VOTES	0	0	0	0	0	0
	FERRARI	0	0	0	0	0	1
	ASTON_MARTIN	0	0	0	0	0	0
	CHEVROLET	0	0	0	0	0	1
	FORD	0	0	0	0	0	0
	JAGUAR	0	0	0	0	0	0
	MERCEDES	0	0	0	0	0	0
	PORSCHE	0	0	0	0	0	0
	OTHER_BRAND	0	0	0	0	1	1
	BRAND_EXTINCTATSALE	0	0	0	0	0	0

Appendix H – Descriptive statistics; characteristics of the sale

The table below includes number of observations for all variables, minimum observation, maximum observation, mean and standard deviation. Percentiles included below. If the mean of a dummy variable with value ‘0’ or ‘1’ is X, that means for X percent of the cases the dummy variable is 1.

Descriptive Statistics						
	N	Minimum	Maximum	Sum	Mean	Std. Deviation
JANUARY	1200	0	1	142	0.12	0.323
FEBRUARY	1200	0	1	65	0.05	0.226
MARCH	1200	0	1	70	0.06	0.234
APRIL	1200	0	1	110	0.09	0.289
MAY	1200	0	1	146	0.12	0.327
JUNE	1200	0	1	136	0.11	0.317
JULY	1200	0	1	77	0.06	0.245
AUGUST	1200	0	1	167	0.14	0.346
SEPTEMBER	1200	0	1	60	0.05	0.218
OCTOBER	1200	0	1	81	0.07	0.251
NOVEMBER	1200	0	1	68	0.06	0.231
DECEMBER	1200	0	1	78	0.07	0.247
BARRET_JACKSON	1200	0	1	131	0.11	0.312
BONHAMS	1200	0	1	188	0.16	0.364
BROOKS	1200	0	1	59	0.05	0.216
KRUSE	1200	0	1	66	0.06	0.228
CHRISTIES	1200	0	1	129	0.11	0.31
McCORMICK	1200	0	1	51	0.04	0.202
MECUM_AUCTIONS	1200	0	1	89	0.07	0.262
RM_AUCTIONS	1200	0	1	148	0.12	0.329
EBAY	1200	0	1	46	0.04	0.192
OTHER_AUCTIONHOUSE	1200	0	1	293	0.24	0.43
Valid N (listwise)	1200					

Percentiles								
		Percentiles						
		5	10	25	50	75	90	95
Weighted Average(Definition 1)	JANUARY	0	0	0	0	0	1	1
	FEBRUARY	0	0	0	0	0	0	1
	MARCH	0	0	0	0	0	0	1
	APRIL	0	0	0	0	0	0	1
	MAY	0	0	0	0	0	1	1
	JUNE	0	0	0	0	0	1	1
	JULY	0	0	0	0	0	0	1
	AUGUST	0	0	0	0	0	1	1
	SEPTEMBER	0	0	0	0	0	0	0.95
	OCTOBER	0	0	0	0	0	0	1
	NOVEMBER	0	0	0	0	0	0	1
	DECEMBER	0	0	0	0	0	0	1
	BARRET_JACKSON	0	0	0	0	0	1	1
	BONHAMS	0	0	0	0	0	1	1
	BROOKS	0	0	0	0	0	0	0
	KRUSE	0	0	0	0	0	0	1
	CHRISTIES	0	0	0	0	0	1	1
	McCORMICK	0	0	0	0	0	0	0
	MECUM_AUCTIONS	0	0	0	0	0	0	1
	RM_AUCTIONS	0	0	0	0	0	1	1
	EBAY	0	0	0	0	0	0	0
	OTHER_AUCTIONHOUSE	0	0	0	0	0	1	1

Appendix I - Overview of differences between respective models introduced in chapter 3

This table shows the differences between the basic models from Chapter 3. Model (1) only includes the year dummies. model (2) includes the year dummies and tangible characteristics of the car. model (3) adds the intangible characteristics of the car and the main model (4) includes all the independent variables. The dependent variable is always LN_REAL2011$PRICE. The variables DISPLACEMENT and DESIGNERS_TOP10 are left out of the model because they showed too much overlap with HORSEPOWER and DESIGNERS_VOTES respectively. The variables MY_AFTER_1980. BLACK. CONDITION#4. MERCEDES. JANUARY and McCORMICK are left out to avoid the dummy variable trap of perfect multicollinearity.

Model	**(1)**	**(2)**	**(3)**	**(4)**
Adjusted R^2	**0.012**	**0.538**	**0.599**	**0.637**
Year Dummies	Yes	Yes	Yes	Yes
Tangible characteristics of the car				
DISPLACEMENT	[Left out]	[Left out]	[Left out]	[Left out]
HORSEPOWER	No	Yes	Yes	Yes
FOUR_CYLINDER	No	Yes	Yes	Yes
SIX_CYLINDER	No	Yes	Yes	Yes
EIGHT_CYLINDER	[Left out]	[Left out]	[Left out]	[Left out]
TWELVE_CYLINDER	No	Yes	Yes	Yes
OTHER_CYLINDER	No	Yes	Yes	Yes
FORCED_INDUCTION	No	Yes	Yes	Yes
ODOMETER_KM	No	Yes	Yes	Yes
MY_BEFORE_1950	No	Yes	Yes	Yes
MY_1950_1980	No	Yes	Yes	Yes
MY_AFTER_1980				
BLACK	[Left out]	[Left out]	[Left out]	[Left out]
BLUE	No	Yes	Yes	Yes
GREEN	No	Yes	Yes	Yes
RED	No	Yes	Yes	Yes
SILVER	No	Yes	Yes	Yes
WHITE	No	Yes	Yes	Yes
YELLOW	No	Yes	Yes	Yes
OTHER_COLOR	No	Yes	Yes	Yes
CONDITION#1	No	Yes	Yes	Yes
CONDITION#2	No	Yes	Yes	Yes
CONDITION#3	No	Yes	Yes	Yes
CONDITION#4	[Left out]	[Left out]	[Left out]	[Left out]
CONDITION#5	No	Yes	Yes	Yes

Model	(1)	(2)	(3)	(4)
RACE_CAR	No	Yes	Yes	Yes
REPLICA	No	Yes	Yes	Yes
Intangible characteristics of the car				
DESIGNERS_TOP10	[Left out]	[Left out]	[Left out]	[Left out]
DESIGNERS_VOTES	No	No	Yes	Yes
FERRARI	No	No	Yes	Yes
ASTON_MARTIN	No	No	Yes	Yes
CHEVROLET	No	No	Yes	Yes
FORD	No	No	Yes	Yes
JAGUAR	No	No	Yes	Yes
MERCEDES	[Left out]	[Left out]	[Left out]	[Left out]
PORSCHE	No	No	Yes	Yes
OTHER_BRAND	No	No	Yes	Yes
BRAND_EXTINCT_AT_SALE	No	No	Yes	Yes
Characteristics of the sale				
JANUARY	[Left out]	[Left out]	[Left out]	[Left out]
FEBRUARY	No	No	No	Yes
MARCH	No	No	No	Yes
MAY	No	No	No	Yes
JUNE	No	No	No	Yes
JULY	No	No	No	Yes
AUGUST	No	No	No	Yes
SEPTEMBER	No	No	No	Yes
OCTOBER	No	No	No	Yes
NOVEMBER	No	No	No	Yes
DECEMBER	No	No	No	Yes
BARRET_JACKSON	No	No	No	Yes
BONHAMS	No	No	No	Yes
BROOKS	No	No	No	Yes
KRUSE	No	No	No	Yes
CHRISTIES	No	No	No	Yes
McCORMICK	[Left out]	[Left out]	[Left out]	[Left out]
MECUM_AUCTIONS	No	No	No	Yes
RM_AUCTIONS	No	No	No	Yes
EBAY	No	No	No	Yes
OTHER_AUCTIONHOUSE	No	No	No	Yes

Appendix J – Cross-tabs to check for whether the big name auction houses simply sell the best products

To get some idea whether the big name auction houses manage to sell for the best prices because of reputation or simply because they sell the best products. some crosstabs are calculated for three characteristics. CONDITION#1. DESIGNER_VOTES and TWELVE_CYLINDER that have shown to drive prices quite hard. If it would turn out that these auction houses sell a lot more of these cars relative to the other auction houses that might have hinted that it's the cars that add the value. not the auction houses. However. this doesn't seem to be the case at all. at least not on the basis if these three variables. Only Christie's seems to sell a bit more cars that fall in the DESIGNER_VOTES categories than all the other auction houses but other than that the numbers are remarkably similar considering these three auction houses achieve the best sale prices.

Kolom1	Kolom2	Crosstab	Kolom3	Kolom4	Kolom5
			CONDITION#1		
			0	1	Total
BARRET_JACKSON	0	Count	857	212	1069
		% within CONDITION#1	88.30%	92.60%	89.10%
	1	Count	114	17	131
		% within CONDITION#1	11.70%	7.40%	10.90%
Total		Count	971	229	1200
		% within CONDITION#1	100.00%	100.00%	100.00%
			DESIGNERS_VOTES		
			0	1	Total
BARRET_JACKSON	0	Count	1004	65	1069
		% within DESIGNERS_VOTES	89.00%	90.30%	89.10%
	1	Count	124	7	131
		% within DESIGNERS_VOTES	11.00%	9.70%	10.90%
Total		Count	1128	72	1200
		Crosstab			
			TWELVE_CYLINDER		
			0	1	Total
BARRET_JACKSON	0	Count	901	168	1069
		% within TWELVE_CYLINDER	88.90%	89.80%	89.10%
	1	Count	112	19	131
		% within TWELVE_CYLINDER	11.10%	10.20%	10.90%
Total		Count	1013	187	1200
		% within TWELVE_CYLINDER	100.00%	100.00%	100.00%

		Crosstabs			
		Crosstab			
			CONDITION#1		
			0	1	Total
CHRISTIES	0.00%	Count	865	206	1071
		% within CONDITION#1	89.10%	90.00%	89.30%
	100.00%	Count	106	23	129
		% within CONDITION#1	10.90%	10.00%	10.80%
Total		Count	971	229	1200
		% within CONDITION#1	100.00%	100.00%	100.00%
		Crosstab			
			DESIGNERS_VOTES		
			0	1	Total
CHRISTIES	0	Count	1020	51	1071
		% within DESIGNERS_VOTES	90.40%	70.80%	89.30%
	1	Count	108	21	129
		% within DESIGNERS_VOTES	9.60%	29.20%	10.80%
Total		Count	1128	72	1200
		% within DESIGNERS_VOTES	100.00%	100.00%	100.00%
		Crosstab			
			TWELVE_CYLINDER		
			0	1	Total
CHRISTIES	0	Count	910	161	1071
		% within TWELVE_CYLINDER	89.80%	86.10%	89.30%
	1	Count	103	26	129
		% within TWELVE_CYLINDER	10.20%	13.90%	10.80%
Total		Count	1013	187	1200
		% within TWELVE_CYLINDER	100.00%	100.00%	100.00%

		Crosstab			
			CONDITION#1		
			0	1	Total
BARRET_JACKSON	0	Count	857	212	1069
		% within CONDITION#1	88.30%	92.60%	89.10%
	1	Count	114	17	131
		% within CONDITION#1	11.70%	7.40%	10.90%
Total		Count	971	229	1200
		% within CONDITION#1	100.00%	100.00%	100.00%
			DESIGNERS_VOTES		
			0	1	Total
RM_AUCTIONS	0	Count	989	63	1052
		% within DESIGNERS_VOTES	87.70%	87.50%	87.70%
	1	Count	139	9	148
		% within DESIGNERS_VOTES	12.30%	12.50%	12.30%

Total		Count	1128	72	1200
		% within DESIGNERS_VOTES	100.00%	100.00%	100.00%

Crosstab

			TWELVE_CYLINDER		
			0	1	Total
RM_AUCTIONS	0	Count	894	158	1052
		% within TWELVE_CYLINDER	88.30%	84.50%	87.70%
	1	Count	119	29	148
		% within TWELVE_CYLINDER	11.70%	15.50%	12.30%
Total		Count	1013	187	1200
		% within TWELVE_CYLINDER	100.00%	100.00%	100.00%

Appendix K - Parameter estimates and implied price impact figures for model (4)

This table shows the coefficients (B) and p-values for the independent variables included in model (4) except the year dummies. after regression on the dependent variable LN_REAL2011$PRICE. The price impact figure is calculated by taking the exponent of the regression coefficient and subtracting 1.

Model (4) Parameter estimates and Price Impact

Variable	B	P Value	Price Impact
HORSEPOWER	.003	.000	0.35%
FOUR_CYLINDER	-.090	.460	-8.60%
SIX_CYLINDER	.302	.001	35.30%
TWELVE_CYLINDER	.427	.000	53.21%
OTHER_CYLINDER	.101	.596	10.59%
FORCED_INDUCTION	.259	.012	29.50%
ODOMETER_KM	.000	.000	0.00%
MY_BEFORE_1950	1.467	.000	333.41%
MY_1950_1980	.513	.000	67.04%
BLUE	.072	.508	7.50%
GREEN	-.080	.538	-7.66%
RED	-.008	.932	-0.83%
SILVER	.186	.128	20.47%
WHITE	-.156	.190	-14.40%
YELLOW	-.033	.819	-3.23%
OTHER_COLOR	.024	.834	2.43%
CONDITION#1	1.065	.000	190.20%
CONDITION#2	.592	.000	80.75%
CONDITION#3	.236	.059	26.64%
CONDITION#5	-.059	.901	-5.73%
RACE_CAR	.808	.005	124.37%
REPLICA	.252	.283	28.68%
DESIGNERS_VOTES	.518	.000	67.88%
FERRARI	.165	.264	17.97%

Variable	B	P Value	Price Impact
ASTON_MARTIN	.016	.927	1.59%
CHEVROLET	-.692	.000	-49.92%
FORD	-.643	.000	-47.43%
JAGUAR	-.852	.000	-57.33%
PORSCHE	-.150	.398	-13.94%
OTHER_BRAND	-.431	.001	-34.99%
BRAND_EXTINCTATSALE	-.171	.178	-15.69%
FEBRUARY	.061	.719	6.25%
MARCH	-.058	.688	-5.65%
APRIL	-.275	.034	-24.01%
MAY	-.059	.650	-5.71%
JUNE	-.140	.279	-13.07%
JULY	-.282	.055	-24.54%
AUGUST	.323	.010	38.19%
SEPTEMBER	-.437	.008	-35.43%
OCTOBER	.171	.247	18.62%
NOVEMBER	-.055	.756	-5.32%
DECEMBER	-.177	.255	-16.19%
BARRET_JACKSON	.624	.003	86.58%
BONHAMS	.377	.049	45.82%
BROOKS	.526	.034	69.20%
KRUSE	.421	.031	52.30%
CHRISTIES	.847	.000	133.21%
MECUM_AUCTIONS	.432	.028	53.98%
RM_AUCTIONS	.616	.001	85.19%
EBAY	.470	.030	59.97%
OTHER_AUCTIONHOUSE	.341	.061	40.70%
a. Dependent Variable: LN_REAL2011$PRICE			

Appendix L - Price Index based on Model (4)

This table shows the coefficients and p-values on the year dummies for model (4) following regression on the dependent variable LN_REAL2011$PRICE. The price impact figure is calculated by taking the exponent of the regression coefficient and subtracting 1. The index is calculated by setting the index equal to '100' for the base year 1996 and subsequently calculating the index numbers for subsequent years using the price impact figures.

YEAR	Coefficient on year dummy	p-value	Price Impact	INDEX	RETURN
1996			0	100.00	
1997	.310	.249	36.31%	136.31	36.31%
1998	.891	.002	143.84%	243.84	78.89%
1999	.330	.186	39.07%	139.07	-42.97%
2000	.478	.048	61.21%	161.21	15.92%
2001	.465	.052	59.27%	159.27	-1.20%
2002	.410	.089	50.65%	150.65	-5.42%
2003	.506	.033	65.80%	165.80	10.06%
2004	.405	.090	49.86%	149.86	-9.62%
2005	.778	.002	117.69%	217.69	45.26%
2006	.394	.096	48.27%	148.27	-31.89%
2007	.477	.049	61.19%	161.19	8.71%
2008	.693	.004	100.00%	200.00	24.08%
2009	.568	.020	76.44%	176.44	-11.78%
2010	.685	.005	98.39%	198.39	12.44%
2011	1.239	.000	245.22%	345.22	74.01%
Geometric mean real return					13.52%
Volatility					34.45%

Appendix M – Price index on Winsorized data

Price Index based on Model (4). except with dependent variable LN_REAL2011$PRICE winsorized to LN_REAL11$WINSOR

YEAR	Coefficient on year dummy	p-value	Price Impact	INDEX	RETURN
1996				100.00	
1997	.294	.265	34.18%	134.18	34.18%
1998	.875	.002	139.86%	239.86	78.77%
1999	.325	.185	38.37%	138.37	-42.31%
2000	.468	.049	59.62%	159.62	15.36%
2001	.458	.051	58.11%	158.11	-0.95%
2002	.399	.091	49.10%	149.10	-5.70%
2003	.491	.035	63.43%	163.43	9.62%
2004	.385	.100	46.96%	146.96	-10.08%
2005	.760	.002	113.77%	213.77	45.46%
2006	.382	.100	46.54%	146.54	-31.45%
2007	.467	.050	59.46%	159.46	8.82%
2008	.660	.005	93.57%	193.57	21.39%
2009	.552	.021	73.69%	173.69	-10.27%
2010	.648	.007	91.12%	191.12	10.04%
2011	1.163	.000	219.88%	319.88	67.37%
Geometric mean real return					12.68%
Volatility					33.33%

Appendix N - The Adjacent-Period approach

The table below shows a price index for collector cars constructed with the adjacent period approach. The dependent variable is LN_REAL2011$PRICE and all the independent variables are included as in model (4). although for some coupled years some variables drop out as they are not represented in the database in the respective biennium. Unfortunately some values seem to be so far off of what they should be that the index provides what are likely to be severely overstated results and volatility. To illustrate: between 1999 and 2010 the index yields a 12.77% return with 26.78% volatility, which would seem to be a lot better in line with the general trend of the other observations in this study.

YEAR	Coefficient on year dummy	p-value	Price Impact	INDEX
1996				100.00
1997	1.023	0.143	178.15%	278.15
1998	2	0.461	638.91%	2055.29
1999	0.392	0.388	47.99%	3041.69
2000	0.268	0.219	30.73%	3976.55
2001	-0.034	0.843	-3.34%	3843.62
2002	0.086	0.687	8.98%	4188.80
2003	0.207	0.14	23.00%	5152.15
2004	-0.108	0.267	-10.24%	4624.72
2005	0.465	0.009	59.20%	7362.61
2006	-0.446	0.014	-35.98%	4713.43
2007	0.032	0.78	3.25%	4866.69
2008	0.183	0.178	20.08%	5844.00
2009	-0.136	0.505	-12.72%	5100.89
2010	0.201	0.513	22.26%	6236.47
2011	0.872	0.07	139.17%	14915.71
Geometric mean real return				73.96%
Volatility				166.28%

Appendix O - Dependent variable substitution

Price Index when the dependent variable in model (4) is changed from LN_REAL2011$PRICE to LN_REAL2011EUROPRICE. In the upmost right column. the index for model (4) is given for the benefit of comparison. Both yield similar results.

YEAR	Coefficient on year dummy	p-value	Price Impact	INDEX	RETURN	Original Model 4
1996			0	100.00		100
1997	.448	.099	56.47%	156.47	56.47%	136.31
1998	1.035	.002	181.45%	281.45	79.88%	243.84
1999	.519	.186	67.96%	167.96	-40.32%	139.07
2000	.824	.048	127.90%	227.90	35.69%	161.21
2001	.843	.052	132.23%	232.23	1.90%	159.27
2002	.729	.089	107.39%	207.39	-10.70%	150.65
2003	.638	.033	89.25%	189.25	-8.75%	165.8
2004	.446	.090	56.14%	156.14	-17.50%	149.86
2005	.829	.002	129.16%	229.16	46.77%	217.69
2006	.444	.096	55.91%	155.91	-31.97%	148.27
2007	.454	.049	57.39%	157.39	0.95%	161.19
2008	.575	.004	77.80%	177.80	12.97%	200
2009	.539	.020	71.48%	171.48	-3.56%	176.44
2010	.691	.005	99.53%	199.53	16.36%	198.39
2011	1.164	.000	220.14%	320.14	60.45%	345.22
Geometric mean real return					13.24%	13.52%
Volatility					35.51%	34.45%

Appendix P - Dependent variable substitution II

Price Index when the dependent variable in the model (4) is changed from LN_REAL2011$PRICE to LN_NOMINAL$PRICE. In the upmost right column provides the identical index for model (4) after ex post discounting of the index from the adapted model.

YEAR	Coefficient on year dummy	p-value	Price Impact	INDEX NOM	Disc Factor	Index REAL	RETURN	INDEX Mod (4)
1996				100.00		100.00		100
1997	.332	.217	39.36%	139.36	0.98	136.31	36.31%	136.31
1998	.929	.001	153.07%	253.07	0.96	243.84	78.89%	243.84
1999	.390	.118	47.70%	147.70	0.94	139.07	-42.97%	139.07
2000	.569	.019	76.69%	176.69	0.91	161.21	15.92%	161.21
2001	.590	.014	80.33%	180.33	0.88	159.27	-1.20%	159.27
2002	.551	.022	73.43%	173.43	0.87	150.65	-5.42%	150.65
2003	.663	.005	94.14%	194.14	0.85	165.80	10.06%	165.8
2004	.588	.014	80.09%	180.09	0.83	149.86	-9.62%	149.86
2005	.997	.000	171.12%	271.12	0.80	217.69	45.26%	217.69
2006	.650	.006	91.63%	191.63	0.77	148.27	-31.89%	148.27
2007	.763	.002	114.39%	214.39	0.75	161.19	8.71%	161.19
2008	1.008	.000	174.00%	274.00	0.73	200.00	24.08%	200
2009	.883	.000	141.72%	241.72	0.73	176.44	-11.78%	176.44
2010	1.020	.000	177.35%	277.35	0.72	198.39	12.44%	198.39
2011	1.605	.000	397.84%	497.84	0.69	345.22	74.01%	345.22
Geometric mean real return						0.00	13.52%	13.52%
Volatility						0.00	34.45%	34.45%

Appendix Q - Comparing CCI with other assets

In comparison with the other assets the CCI holds up pretty well at first sight. only long term US Treasuries enjoy a significantly higher Sharpe ratio.

Mean Real Log Returns from 1996-2011	Kolom1	Kolom2	Kolom3
Asset	Mean	Volatility	Sharpe Ratio
Treasury securities at 10-year constant maturity (TS10M)	0.019	0.004	0.92
3 Month Treasury Bills (3MTUS)	0.015	0.007	0.00
MSCI USA (MSCIUS)	0.026	0.099	0.11
MSCI EUROPE (MSCIEUR)	0.025	0.113	0.08
MSCI UK (MSCIUK)	0.016	0.078	0.01
MSCI WORLD Index (MSCITK)	0.018	0.098	0.03
MSCI EUROPE REAL ESTATE $ - PRICE INDEX (MSCIERE)	0.016	0.144	0.01
S&P GSCI Commodity Spot - PRICE INDEX S&P Com (S&PCOM)	0.034	0.101	0.19
S&P GSCI Four Energy Commodities Spot - PRICE INDEX (S&PNRG)	0.043	0.130	0.21
Collector Car Price Index (CCI)	0.036	0.136	0.15

Appendix R - Correlation between the CCI and other indices

TS10M is short for the long term US Treasury bonds. 3MTUS designate the 3-month US T-bills. MSCIUS. MSCIEUR and MSCIUK are the US. European and UK MSCI Indices respectively. MSCITK is the MSCI world index. MSCIERE is the MSCI European Real Estate Index. S&PCOM and S&PRNG are the S&P's commodity index and S&P's index on four energy commodities. Finally the CCI is the Collector Car Index. The CCI shows a negative correlation with the bond indices and the commodity indices and positive correlation with the stock indices and European real estate market.

	TS10M	3MTUS	MSCIUS	MSCIEUR	MSCIUK	MSCITK	MSCIERE	S&PCOM	S&PNRG	CCI
TS10M	1									
3MTUS	0.959266	1								
MSCIUS	0.493394	0.587277	1							
MSCIEUR	0.322226	0.452663	0.946244	1						
MSCIUK	0.399465	0.500631	0.960501	0.93271336	1					
MSCITK	0.33411	0.461	0.961073	0.98435613	0.9458554	1				
MSCIERE	0.248975	0.290274	-0.138885	-0.2262804	-0.145181	-0.175218	1			
S&PCOM	-0.05999	-0.02667	0.016298	0.07990177	-0.011274	0.040508	0.3226432	1		
S&PNRG	0.07031	0.090747	0.105408	0.14143651	0.0529835	0.089915	0.2448168	0.97149005	1	
CCI	-0.17581	-0.13489	0.180143	0.16088045	0.1365438	0.191042	0.2559217	-0.0356763	-0.119628	1

Appendix S - The place of collector cars in investment portfolios

In Specification 1 all the assets are included with equal weight (10%). In the other specifications the weights are left to the software. unless otherwise specified. In specification 2 the software advises to spend 2% of the investment portfolio on investments in collector cars. In Specification 4 the 10% CCI is a given constraint. In none of the cases shorting was allowed.

Asset	Specification 1	Specification 2	Specification 3	Specification 4
TS10M	0.100	0.955	0.882	0.846
3MTUS	0.100	0.000	0.118	0.000
MSCIUS	0.100	0.000	0.000	0.000
MSCIEUR	0.100	0.000	0.000	0.000
MSCIUK	0.100	0.000	0.000	0.000
MSCITK	0.100	0.000	0.000	0.000
MSCIERE	0.100	0.000	0.000	0.000
S&PCOM	0.100	0.000	0.000	0.000
S&P NRG	0.100	0.025	0.000	0.054
CCI	0.100	0.020	0.000	0.100
$\sum w_i$	1.000	1.000	1.000	1.000
μ	0.025	0.020	0.019	0.022
σ portfolio	0.052	0.004	0.000	0.014
sharpe prtf	0.19	1.24	#DEEL/0!	0.48

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