CHARLES UNIVERSITY
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Impact of Electric Vehicles adoption on automotive companies stock performance

Master's thesis

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Year of defense: 2021

Declaration of Authorship

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Prague, July 27, 2021

Petra Suntychova

Abstract

This thesis investigates the relationship between asset prices and their sensitivity on electric vehicles adoption using methods of a factor analysis with portfolio sorts and Fama-French three factor model. We test whether there is a monotonic relationship between an asset sensitivity to electric vehicles adoption changes. For the factor construction a data set with monthly car sales data grouped by model type is used. The study provides an empirical evidence that there is a significant monotonic relationship between sensitivity with asset sensitivity on electric vehicles adoption and stock price performance. The analysis confirms that stocks with higher sensitivity to electric vehicles adoption earn lower returns.

JEL Classification	F12, F21, F23, H25, H71, H87
Keywords	Fama-French, electromobility, factors, factor analysis

Title	Impact of Electric Vehicles adoption on automotive companies stock performance

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Abstrakt

Tato bakalářská práce zkoumá specificka vztahu mezi výnosností aktiva a jeho citlivostí na adopci elektrických vozidel za pomoci metody faktorové analýzy spolu s portfolio sorts a Fama-French třífaktorovým modelem. Testujeme, zda existuje monotonní vztah mezi citlivostí aktiva na faktor adopce elektrických vozidel. Ke zkounstruování faktoru byl použit dataset s mesíčními prodejními daty podle modelového typu vozu. Práce poskytuje empirickou evidenci, že existuje signifikantní monotonní vztah mezi citlivostí aktiva na faktor EV adopce a jeho výnosností. Analýza potvrzuje, že aktiva s vyšší citlivostí mají menší výnosy.

Klasifikace JEL F12, F21, F23, H25, H71, H87
Klíčová slova Fama-French, elektromobilita, faktory, analýza faktoru

Název práce Analýza výkonnosti akcií automobilových společností na základě jejich podílu prodeje elektrických vozidel

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Acknowledgments

The author is grateful especially to Mgr. Jan Šíla, MSc.for his patience with her and for all his useful comments regarding the direction of the analysis.

Typeset in FSV LaTeX template with great thanks to prof. Zuzana Havrankova and prof. Tomas Havranek of Institute of Economic Studies, Faculty of Social Sciences, Charles University.

Bibliographic Record

Suntychova, Petra: *Impact of Electric Vehicles adoption on automotive companies stock performance.* Master's thesis. Charles University, Faculty of Social Sciences, Institute of Economics and Finance, Prague. 2021, pages 45. Advisor: Mgr. Jan Šíla, MSc.

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Acronyms

EV Electric Vehicle

HEV Hybrid electric vehicle

PHEV Plug-in Hybrid Electric Vehicle

Master's Thesis Proposal

Author	Petra Suntychová
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Proposed topic	Impact of Electric Vehicles adoption on automotive companies stock performance

Motivation Electric vehicles are currently the focus of the majority of car manufacturing companies, at least to some extent. On the one hand, there are manufacturers focused solely on electric automobiles since they were established. On the other hand, there are companies currently investing in the shift from combustion engine powered vehicles to electric ones. Even though strategies of stakeholders might be mixed (Bakker, S., Maat, K., van Wee, B. (2014)). Some of these companies even introduced their plans to produce fully electric automobiles only, which might be interpreted as that these companies consider all-electric vehicles the future of transportation.

The EV market is influenced by government incentives along with consumers characteristics (Makena Coffman, Paul Bernstein Sherilyn Wee (2017)). All these influences result in a disproportional market share of automotive companies in the electric vehicles market. The intent of the thesis is to answer how significant impact does the market share of electric vehicles have on car manufacturersâ€™ stock performance.

Hypotheses

Hypothesis #1: The literature estimating gasoline demand elasticities is affected by publication bias.

Hypothesis #2: The publication bias exaggerates the mean reported elasticity.

Hypothesis #3: The extent of publication bias decreases in time.

Methodology Dataset consisting of time-series sales data of all major automotive companies for last 10 year will be used along with Kenneth Frenchâ€™s Data Library.

Automotive companies will be sorted into 3 portfolios based on their ratio of electric vehicle sales compared to their overall personal car sales. Portfolios will be rebalanced monthly. For each company every day will be estimated a regression with excess return as dependent variable and excess return on the market portfolio and EVs sales ratio as independent variables. Annual returns as summed daily returns will be the alpha of Fama French three-factor model. Based on the factor model, a stock return premium, potentionally explainable by investorsâ€™ desire to invest into more ecological and sustainable solutions, will be obtained.

The null hypothesis saying that there is no relationship between electric vehicles sales ratio and portfolio performance will then be tested.

Expected Contribution To the best of my knowledge, this thesis is the first analysis focusing on companyâ€™s sales share of electric vehicles on its stock performance but research studying other aspects of EVs market, such as how it is affected by the price of lithium used for batteries production published by Baur et al. in 2018 or which determinants have a significant effect of EVs adoption studied by Soltani-Sobh et al. (2017). It can be predicted that the research will follow as some manufacturers already introduced their plans to produce cars with electric engines only in the future along with policies positively discriminating electric vehicles.

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Author Supervisor

Chapter 1

Introduction

Climate change prevention and an environment conservation are topics being discussed by public now more intensively than ever. Multiple approaches are being implemented in order to decrease a negative impact of human population on the nature. One of key approaches towards this goal is to limit the amount of harmful substances in the air and decrease a fossil fuel consumption by lowering the number of vehicles with combustion engines processing fossil fuels. There are many ways of how to approach this problem and a substitution of fossil-fuel powered vehicles with electric ones is definitely one of them.

The outlook published by IEA (Glo) shows the electric car stock development with not even a million cars in 2010 and over 7 million vehicles in 2019. Figures provided in the report show that vehicles adoption is currently on its rise with a growth exceeding linearity and also confirms that electric vehicles are becoming an important alternation to vehicles with non-electric combustion engines.

There are two reason why electric vehicles are being promoted as an conscious option for mobility. Firstly, even though there may use electricity obtained from burning fossil fuels in case no renewable resources option is available, they are not dependent on them. The second reason is that electric vehicles do not release harmful substances such as carbon dioxide, an oxide responsible for a greenhouse effect, directly into the atmosphere. This is an important fact for city residents with higher vehicles concentration density, for example.

Automotive producers are currently being motivated to focus on this segment of mobility more than ever. From the EU's plan to invest tens of million euros in the Europe-wide electric mobility initiative (Ele) it is possible to see not only that consumers are more willing to invest in electrification of their car fleet now but also, governments with the European union in the leading position are currently using regulations and incentives in order to strengthen the position of electric vehicles on the market.

This setup provides an opportunity for both new and already established car manufacturers. Even though there are still automakers with no vehicles using alternative-fuels engines in their portfolio, majority of them have at least invested in their electric mobility research and development departments already and introduced their plan to produce some kind of electric vehicles in the future. Apparently, there is not a single approach all manufacturers all companies are pursuing in order to contribute to this new phase of mobility.

Even though there may be many aspects affecting the company stakeholders decision process on whether they should be more interested in the electrification of their portfolio, this thesis investigates how the sensitivity towards changes in electric vehicles adoption by public affects the performance of the asset. For this, a factor analysis on electric vehicles adoption will be used. From this analysis, a certain premium of electric vehicles is obtained. This premium might have multiple explanations, one the them being the ecology premium representing investors willingness to invest in solutions with certain ecological value.

For the previously described analysis, a factor model method will be used. After the EV adoption factor is constructed based on U.S. monthly sales data, method of portfolio sorts is implemented with assets sorted into equally weighted terciles based on their estimated sensitivity on the previously created factor with rolling window of 2 months. Excess returns of these portfolios are then regressed on portfolio alpha, being the intercept from previous rolling regression and factors included in the Fama-French three factors, for which the data was downloaded from Kenneth French website. Results will then be compared across previously sorted portfolios and studied for their significance. The intercept difference of portfolios with the highest and lowest sensitivity to EV factor represents the portfolio strategy premium, interpreted as the premium obtained from redistribution of resources from the one portfolio to another.

Since factors are used to reveal an underlying relationship, it is possible to discuss, based on result of our analysis, which underlying relationship are reflected in the EV adoption factor, what might be the explanation of these results and what learning it brings.

Chapter 2

The Electric Vehicles Market

2.1 Electric vehicles characteristics

Electric vehicles is a summary designation of all vehicles using one or more electric or traction motors for propulsion. They can be powered either by an electricity from off-vehicle sources or be self-contained with rechargeable batteries, solar panels, etc. Personal electric vehicles are usually powered by self-contained, rechargeable batteries.

Electric vehicles, being a part of alternative fuel vehicles, include multiple subgroups divided based on included engine types, such as plug-in hybrid electric vehicles (PHEV), hybrid electric vehicles (HEV), battery electric vehicles (BEV), and others. All electric vehicles consist of an electric motor driven by a battery. For the purpose of this thesis, the author decided to pursue a currently popular approach of considering only BEVs and PHEVs to be classified as electric vehicles. The reasoning behind this decision is that hybrid vehicles use an electric engine as a complement to the internal combustion engine only, with its battery being charged by recovering the energy created during breaking, which would be lost otherwise. This conflicts with the idea of electric vehicles advantage being their at least partial independence from fossil fuels. Therefore, because the electric engine uses an energy from fossils fuels used by the combustion engine only, hybrid vehicles will be considered primarily fuel-efficient and therefore will not be included in the factor analysis as part of the electric vehicles group.

The main for why electric vehicles are considered to be more environmentally friendly option compared to fossil fuel-powered vehicles is that the electricity for batteries can be generated by multiple resources including renewable resource (solar, wind and tidal power, hydro-power), nuclear power, as well as fossil fuels. Each of these sources has a different level of carbon footprint. Fossil fuels powered combustion engines, on the other hand, s are able to derive their energy from a few, usually non-renewable, fossil fuel sources only. Therefore, combustion engines are completely dependent on fossil fuels and currently have no option of replacing their fossil fuels consumption at least partially with renewable resources option. These differences directly imply that an increased usage of electric vehicles, assuming they are used as a substitute for combustion engines, promises a reduction of locally harmful emissions being released to the atmosphere along with a decrease of fossil fuels dependency.

The ongoing electric vehicles adoption rise in not interesting only because of environmental impacts but also from business point of view. The company Tesla Inc., for example, is a member of Standard and Poors 500 market index, also know as SP 500. With SP 500 being a stock market index that tracks 500 large companies listed on the US stock exchange, Tesla, relatively young company, stands in the portfolio side by side with companies such as Apple Inc., Microsoft, Amazon or Facebook. That is an exceptional result for a company which is not considered to be technological. This is another aspect separating the electric vehicles market from the rest of the automotive industry. This is probably the first time an automotive company, coming from industry usually considered to be rather on the more conservative side of the spectrum, has the PR power necessary to deflect a cryptocurrency price so dramatically as Tesla Inc. did. Another case when lines between automotive technological industry started to be slightly more blurry than usual, is the intensively rumoured project of Apple Car. Even though the product itself should be manufactured by one of automotive producers primarily focused on manufacturing cars powered primarily by fossil fuels, it is another example of an exceptional business act related to electric vehicles.

2.2 The History of Electric Vehicles Development and Adoption

Even though vehicles with engines consuming an electricity might appear to be a new development, they were popular in the late 19th century already. As Burton (2015) states, electric vehicles were the first choice of royalty and high-society drivers back then and the technology of hybrid vehicles promised to solve the most notable issues with these vehicles, including their drive range. But technological issues and inconveniences of vehicles with internal electric engine resulted in decreased demand for these types of cars.

Electric vehicles started to become a serious substitute of fossil fuel powered cars due to the technological development in the 21. century, which allowed all-electric engines to become full substitutes of combustion engines, the leading technology for approximately past 100 years.

Tesla Roadster was the first highway legal serial production all-electric car using lithium-ion batteries and therefore it may be considered the first step in the â€śnew waveâ€ť of electric vehicles. It was launched by Tesla Motors EV company in 2008 and there were about 2.5 thousand pieces sold worldwide in total. Similarly to the 19th century development, the Roadster was considered to be a niche luxury car. Since then, a vast majority of car manufacturer companies introduced their all-electric models. The range of EVs either currently available or at least planned to release in relatively near future includes a vast majority of vehicle categories from sports cars to sedans, off-roads or vans.

2.3 Determinants of electric vehicles adoption

Incentives for electric vehicles adoption by customers are coming from multiple sources, as well as similar incentives for car manufacturers. Increasing market share of EVs confirms that these incentives are effective. There are multiple advantages and disadvantages consumers state to be the main drivers during the decision process of whether to select an EV or a car with an internal combustion engine only.

The issues reported by customers with EV puchases the most frequently are high upfront purchase costs, insufficient driving range, a lack of charging infrastructure and an engine performance gap, as descibed by Coffman *et al.* (2017), Rezvani *et al.* (2015) and Brase (2019). Even though some of these issues persist since the first phase of electric vehicles adoption in 19th century, some of current potential issues might be alleviated by technological development in near future, resulting in likely decrease of the number of these concerns.

On the other hand, an EV ownership possess certain advantages as well, from which some are even counterparts to disadvantages mentioned before. One of the main advantages are decreased usage costs due to electricity price per the same distance are lower than the amount of fossil fuels needed for the same longitude. Even though electric vehicles have usually higher price than their petrol-infused counterparts, a decreased cost of fuel/charging expenses might find out, considering a discounting function of future costs relative to present costs (Carson & Roth Tran 2009), (Hardisty & Weber 2009), that they are better off paying a higher price for an EV, since their decreased month-to-month expenses for charging might offset the price difference in the long run. Therefore, the proportion of people preferring an EV ownership increases directly with total operating costs. Incentives provided by policymakers with the intention of alleviation the front costs might also increase the adoption by practically decreasing the EVs price towards fossil fuel powered vehicles.

The list of advantages enlarges when government and other incentives are accounted for. Many governments are currently trying to incentive both production and adoption of electric vehicles by initiating policies due to the cited importance of fighting climate change, as described by Brady & Oâ€™Mahony (2011). These incentives include not only direct financial subsidies for EV purchases but also EV specific parking policies, or even the permission to enter a city center with a car, for example.

There are other aspects of an EV ownership, which are not able to be quantified directly. According to Egbue & Long (2012), the pro-environmental beliefs, based on the perception of electric vehicles being more environmentally friendly option than fuel-efficient cars, positively affect buyerâ€™s intentions. On the other hand, certain doubts regarding the positive environmental impact of EVs due to inability to produce the electricity from renewable sources in satisfactory amount have been expressed by customers. Schuitema *et al.* (2013)) also state that consumer self-image and cost signalling intentions have been described as another factor affecting consumer behaviour towards EV adoption. Interestingly, the higher price of EVs in this case might even attract customers with certain self-identity preferences.

2.4 Automotive Manufacturers approach to electrification of their portfolio

The trend of electric vehicles adoption necessarily interests car manufacturers as well as the market share of EVs rises. The approach of car manufacturing companies toward electric vehicles varies significantly and it is safe to say that a vast majority of these producers currently experiences certain portfolio transformation towards vehicles powered solely by electric engine. The speed of change in the level of involvement varies dramatically as well.

Aggeri *et al.* (2009) state that the electrification or hybridization of manufacturers portfolio implies large changes in both the technology itself along with change in business models. They also highlight that in this kind of an innovation field, more advanced mechanisms including market experiments, exploratory partnerships and overall learning strategies might be needed for automotive companies aspiring to be leaders in the industry. For a large car manufacturer to exploit an innovation such as the EV, it needs both an incentive and an opportunity to innovate Swann Jr *et al.* (2009). Wesseling *et al.* (2015)suggest that companies with stronger incentive and opportunity to innovate should introduce more EVs into the market in order to become incumbents of the market.

Chapter 3

Data

Three types of data we used for the empirical analysis. Based on data availability, the monthly U.S. sales data including the amount of vehicles sold based on model type obtained form website goodcarbadcar.com in May 2021 were chosen as a data set based on which the factor of interest is constructed. This data set contained an information about approximately 300 car models sold in the U.S. market with monthly frequency. Since data were downloaded in three files, each for one year, they were integrated into a final sheet based on model name.

Based on an information in manufacturers website an information about engine type possibilities were included as a variable in the set with values 1, 0.5 or 0 when a model type is an BEV, PHEV, or any of them respectively. These values can be also viewed as coefficients on model â€śelectrificationâ€ť coefficient as described in previous section. The reasoning behind coefficient 0.5 for PHEVs is that any model included in the data sample can be purchased in PHEV version only, meaning that all of them have fossil fuel-powered engine options available as well. Since there is no data regarding model type and its engine specifications, the author decided to approximate the modelâ€™s fraction of PHEVs sold to be one half. There was one exception regarding these coefficient in Mercedes-Benz models releasing PHEV versions of their portfolio with delay compared to their non-EV counterparts. This irregularity was solved by manual change of respective coefficients in the sample.

Based on the U.S. sales data an EV sales factor was obtained for each month as the total amount of EVs sold (with respective coefficient values added) during the month, divided by the total amount of cars sold during the same time period.

Historical data of daily stock prices for all 17 companies of interest were downloaded from Yahoo Finance with start date on 1st January 2019. Each data table had 7 columns including an information about date, an opening price value that day, highs and lows, volume, and others. For our analysis, only columns with date and adjusted closing price, reflecting stock's value after account for any corporate actions, were used. Stock returns for respective day were calculated as a difference between adjusted closing prices of the stock on respective and previous working day, divided by adjusted closing price of the previous working day. The result was multiplied by 100 in order to obtain percent values.

The third type of data used for the analysis were daily U.S. market factors and returns used for the Fama-French three factor model, downloaded from Kenneth French's data library. Downloaded data set contains the following values for each day:

- Mkt - RF, the difference betweed market value and risk free ration for that day
- SMB - the Small Minus Big factor used to explain portfoliio returns based on the company size
- HML - the High Minus Low factor used to explain portfoliio returns based on the book value-to-market ratio of the company
- RF - the risk free rate for the respective day

Since there is no option to select the date range for which the data set should be downloaded, all values out of the authors time range of interest were deleted in order to match the EV factor data as well as Yahoo Finance data for all companies of our interest. Time frame of the first two data sets were also longer than the time frame of market factors. The data frames were therefore aligned as well, loosing the month of stock returns data.

In order to obtain betas based on which companies should be sorted into portfolios, a rolling regression for asset of each company had to be performed.

Since the rolling window of 2 months was used, the first two months of each data set were lost since the rolling window regression could not be performed for them.

Company assets were then distributed into equally weighted portfolios based on the order of their betas on the first day of each month with ratios 6:7:6. Portfolio returns were calculated for each obtained portfolio each each month as sum of monthly returns of each company included in the portfolio with respective weights, which in our case were 1 over n with n being the number of assets included in each portfolio.

Finally, monthly excess returns of each portfolio were regressed on their respective alphas obtained in previous phases of the analysis, the EV factor values created previously and Fama-French factor values as independent variables.

Chapter 4

Methodology

4.1 Linear Regression

In the methodology part of the thesis, we will firstly focus on a linear regression used for evaluation or linear models. The regression analysis is considered to be one of the most popular techniques used for multi-factor data analysis and the author believes it is important to mention its basic concepts as they will be used later on in the analysis.

As in Wooldridge (2009), the simple linear regression is used to study the relationship between two variable, one of them being independent (x) and one dependent (y). Their statistical relationship can be expressed as

$$y = \beta_0 + \beta_1 x + u$$

with betas being regression coefficients. The β_0 is called an intercept and will be interpreted later on as a pricing error of our models. Variable u is called an error and represents the factor variables other than x (variables missing from the equation), which influence the dependent variable.

Certain assumptions need to be fulfilled in order to obtain unbiased results. First of all, it is assumed that the function is linear in its coefficients. Homoskedacity is the second assumption. It says that variance of residuals equals for all X. Also, it is assumed that error terms are uncorrelated. Since betas are linear, the relationship between x and y, with errors fixed, can be represented as a linear line with slope equal to β_1.

The second regression we will perform during our analysis is the multiple linear regression. Concretely, the multiple linear regression will be used while evaluating the Fama-French three factor model. The main difference between simple and multiple linear regressions is that while simple linear regressions have exactly one independent variable x, multiple linear regressions have multiple independent variables x. The statistical relationship between dependent and independent variables can be expressed as

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + +\beta_k x_k + u$$

Similarly to the simple linear regression, betas $\beta_1, \beta_2, ..., \beta_k$ are regression coefficients associated with corresponding independent variables $(x_1, x_2, ..., x_k)$ and β_0 is an intercept. The interpretation of regression coefficients is the expected change of dependent variable when respective independent variable changes by 1 unit, holding other variables constant.

Probably one of the most popular method of estimating unknown parameters based on sample data is the method of ordinary least squares (OLS), which chooses estimates to minimize the sum of squared residuals (Wooldridge 2009). The OLS equation can be expressed as follows:

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + ... + \hat{\beta}_k x_k$$

$\hat{\beta}$s are in this case estimates or the regression and they have ceteris paribus interpretations, meaning that they estimate a change of dependent variable when respective independent variable is changed by one unit, while all other independent variables are held fixed.

Sum of squares are sums or square of variations with variations being spreads between an individual value from the sample and its mean across the whole sample. There are three widely accepted sum of squares measures, being the residual sum of squares (SSR), sum of square explained (SSE) and the total sum of squares (SSR). The SST represents the sum of squares between dependent variables from the sample and its mean. SSE is calculated as sum of squared differences between dependent variable estimates and sample mean. Lastly, the SSR is sum of estimated residuals. Sum of squares values are used to calculate the coefficient of determination R^2, value, which represents the proportion of dependent variable variation, predictable based on independent variables. Values of R-squared always lie in the interval between 0 and 1 and is calculated as SSE divided by SST. From its nature, R-squared is being increased every time a new independent variable is added in the model. Therefore, the informative value or R-squared always needs to evaluated cautiously.

4.2 Multifactor Models for Asset Returns

Multifactor models are trying to explain a return of an asset with multiple factors in its calculation. Its purpose its to describe an underlying risk premium for the risk accepted and its sensitivity to such risk.

As in Connor (1995) multi-factor models of security market can be divided, with some blurring at the boundaries, into three types. These types can be either

- Macroeconomic, for example the percentage change in industrial production, employment, long-term return of government bonds, or an inflation. They are the most intuitive type,as they use observable variables. The description of commonly used macroeconomic factors or equity was described by Chen, Roll and Ross (1986).
- Statistical, which use various statistical methods on either cross-sectional or time-series samples of asset returns in order to identify the factors in return. This is the type our EV factor is. Two methods, the factor analysis and principal component are used to statistical factor models.
- Fundamental factor models, which as the only factor type do not require time-series regression but rather focus on the relationship between an asset return and its empirical company attributes, such as a company size, industry, etc.

Connor (1995) concludes based on an empirical analysis that statistical and fundamental factor models substantially outperform the macroeconomic factor model with the fundamental factor model slightly outperforming the statistical factory model.

The statistical factor model is used in our empirical analysis. Instead of mean-variance optimization, an alternative approach of factor models will be used with the following structure

$$r_{i,t} = \alpha_i + \beta_1 * F_{1,t} + \beta_2 * F_{2,t} + ... + \beta_N * F_{N,t} + \epsilon_{i,t}$$

with the return of asset i at time t on the left side and Fs being the factors with their respective factor loading, betas, measuring the sensitivity of an asset to changes in the factor. ϵ represents the error term. α being the intercept is our main coefficient of interest, as it measures the return of an asset inexplainable by exposure to factors included in the model or company-specific information. Therefore, the α measures the excess return of an asset.

Objectives of this method are an excess return maximization of the portfolio (represented by α), maximize portfolios volatility (therefore, minimize the beta of the portfolio) and being sufficiently diversified, meaning minimizing the impact of a news specific to a single firm.

One solution for the problem described above was proposTreynor & Black (1973). The Treynor-Black models objective is to optimize a Sharpe Ratio of a portfolio by combining an active investment with underpriced securities with an index fund managed passively. The Sharpe Ratio is a measure of risk-adjusted return describing the excess return for the volatility of holding an asset with higher risk. The Sharpe (1966) ratio is calculated as an expected value of an asset return R_a minus its risk free return R_b, divided by the standard deviation of the asset excess return σ_a.

$$S_a = \frac{E[R_a - R_b]}{\sigma_a}$$

4.3 Portfolio Sorts

The method of portfolio sorting is an important tool for empirical finance research. It is mainly used for testing theories in asset pricing and identification of profitable investment strategies. Characteristic-sorted portfolios are portfolios where assets are constructed based on similar values for one or more idiosyncratic characteristics and the cross-section of portfolio returns is of primary interest (Calonico *et al.* 2019). One of reasons why to use portfolio sorts is that they do not require the assumption of linear relationship between expected returns and the factor.

The main reason for use of portfolio sorts is to discover, whether expected returns of an asset are related to a certain sample characteristic. The way portfolio sorts are usually processes is to sort and divide observed asset returns by the characteristic value and compare differences in obtained average returns across those portfolios. Assets are usually grouped into groups based on quantiles in the sorted list. This method produces an intuitive estimator of relationship among sample characteristic and asset returns where the difference between the expected return on the highest and lowest portfolios can be interpreted as a profit from certain trading strategy.

For each time period (t), J disjoint portfolios should be formed. Since observations in portfolios should be distributed equally, it can be said that every portfolio is an interval containing roughly (100/J) percent of observations at each time period t. The amount of portfolios J is unchanged and set by the researcher, whereas the amount of portfolio members can vary over time.

The appropriate choice of the number of portfolios is the most important setting for getting valid empirical conclusions. Optimal choices should optimally balance bias and variance. Cochrane (2011) suggests that the common approach is to keep the choice of the number of portfolios unchanged to the data being analyzed. Usually, the final choice follows historical norms being either 3, 5 or 10 portfolios.

Cattaneo at al. (2019) suggest that there is a data-drive procedure of how to obtain the optimal number of portfolios based on portofolio alpha, information ratio and t-statistics. The optimal result then varies with sample size and should be larger for longer time-series. Since dataset used for the following analysis includes only 15 companies, due to the fact that there are no other publicly traded car manufacturing companies, J will be set to the lowest historical norm, meaning J = 3.

After portfolios are formed, their residuals are estimated for each order statistics of the sample characteristic as a sum of residuals for each time period divided by the number of time periods. The estimator can be obtained using OLS or weighted least squares in case of value-weighted portfolios. It has been documented that for smaller J, the variance of estimated residuals is relatively low due to higher number of samples in each portfolio. It also implies that sample characteristic values are more far from each other, which implies increased bias. On the other hand, higher J implies more inflated variance and decreased bias.

The next step, after portfolios and estimator are defined, are expected returns of the highest portfolio minus expected returns of the lowest one. Results of this substraction can then be either interpreted as a test of monotonicity of the function of residuals or used to construct factors based on studied characteristic. In the monotonicity test it is important to distinguish, whether the expected return of sorted portfolios are monotonically increasing or decreasing. In the case of this paper, the second option will be used as obtained results will be used as a factor in the Fama-French 3 factor model.

4.4 Fama and French Three Factor Model

The Fama-French three-factor model, designed by Eugene Fama and Kenneth French (1993), is an asset pricing model for describing stock returns. Is it considered to be an ancestor of the capital asset pricing model (CAPM), which uses one variable of systematic risk to describe returns of stock or portfolio only.

The CAPM, introduced by Sharpe (1964) and Lintner (1965) is considered to represent the birth of asset pricing theory. It is based on Markowitz *et al.* (1959) model of portfolio choice, which assumes that an investor selects at time t-1 a portfolio producing a stochastic return at t. It assumes investorâ€™s preferences based on mean and variances on investment return at time t together accompanied by his risk aversion, resulting in investor choosing a portfolio minimizing the variance of its return and maximizing the expected return for the variance given. The CAPM model takes the portfolio choice theory and based on its algebraic statement forms the prediction about the relationship between risk and expected return implying that the CAPM identifies portfolios efficient in case asset prices are to clear the market of all assets. Based on FAMA & FRENCH (1992), the version of CAPM by Lintner and Sharpe has never been a success in empirical analysis, since empirical results shows that the relationship between the beta, used as a risk factor in the mean-variance efficient portfolio, and average return is actually flatter than predicted, resulting in CAPM estimates for cost of equity being too high for high beta stocks and too low for low beta stocks. Also, if high average returns on stocks with high book-to-market ratios, known as value stocks, imply high expected return, the

CAPM estimates of cost equity for these stocks are too low.

Volatility is a statistical measure of risk, measuring the dispersion of asset returns over time with assets which returns fluctuate more having a greater risk. The β, included in the CAPM model, is a measure of systematic risk. The unsystematic risk is described as an error term of CAMP estimated by OLS.

The three-factor model, published by FAMA & FRENCH (1992), uses three variables to describe returns of a stock or portfolio instead of one. Fama and French in their paper state that there are other important variables missing in asset-pricing theory. Those missing variables are size ME, being the stock price times number of shares, leverage, earnings/price (E/P) and book-to-market equity, calculated as the ratio of the book value of a firmâ€™s common stock, BE, to its market value, ME. The Fama-French therefore includes variables considering empirical observation high value and small-cap companies statistically tend to outperform the market as whole.

Therefore, their final equation is:

$$r = R_f + \beta_1(R_m - R_f) + \beta_2(SMB) + \beta_3(HML) + \eta$$

Where r is portfolios expected return rate, R_f the risk-free return rate, and R_m describes the return of market portfolio. The beta in Fama-Frenchâ€™s model is only analogous to beta in CAPM, not equal. Abbreviations SMB and HML stand for â€śsmall minus bigâ€ť in sense of market capitalization and â€śhigh minus lowâ€ť for book-to-market ratio. The alpha can be described as an excess return beyond what would be expected considering other factors alone.

The SMB Fama-French factor, also known as Small Minus Big, is a factor explaining portfolio returns taking into consideration company market capitalization, being the total market value of all company's outstanding stock shares. The market capitalization value is calculated as the number of company shares time price per share. The value is also sometimes referred to as a market cap. Companies are based on their market capitalization divided into three groups: large cap companies with market capitalization over 10 billion dollars, mid-cap with capitalization between 2 and 10 billion dollars and small-cap with capitalization in a range between 300 million ad 2 billion dollars. The interpretation behind this factor is that small-cap companies tend to outperform large cap companies. The reasoning behind this is based on the CAPM, evaluating portfolio returns based on its amount of risk. Due to its size, small-cap companies represent increased risk and therefore, their return should be higher.

The HML, known as High Minus Low, Fama-French factor on the other hand represents a variation in returns based on company book-to-market ratio, referring to stocks of companies with high book-to-market ratio as High value. On the other hand, stock of companies with low book-to-market ratio are referred to as Growth stocks The HML factor revealed that stock with high book-to-market ratios in the long run outperform growth stocks. The book-to-market ratio is calculated as shareholder equity divided by market capitalisation. The reasoning behind the HML factor is that companies with high book-to-market ratios have higher probability of experiencing financial distress and therefore be more sensitive to market changes. This results in higher risk being associated by CAPM with higher returns.

Compared to CAPM 70 percent, Fama and French state in their paper from 1992 that their three-factor model explains more the 90 percent of diversified portofolio returns. There have been some remarks regarding Fama-French 3-factor models global reliability by Griffin & Lemmon (2002) or Foye *et al.* (2013).

4.5 t-test

T-tests are important part of regression analysis. They are used on regression coefficients in order to test their significance between group is, preventing a statistical failure to lead the researcher into making assumptions based on coefficient, which occured by a chance.

The t-score is a ratio calculated as the relative difference between medians of two groups and differences within these groups. The smaller the t-score is, the more are those two groups similar. On the other hand less similar groups setup results in higher absolute value of t-score.

The null hypothesis for testing the significance of a certain regression coefficient beta says that the beta equals 0. If we fail to reject the null hypothesis, it is implied that the dependent value related to the beta of interest is not significant for explaining the dependent variable. Researcher can conclude that their failed to reject the null hypothesis if the t-score falls in the interval limited by critical values for two-sided hypothesis.

T-score directly coheres with p-value, representing the probability of results obtained from data sample occurred by chance on scale of 0 to 100 percent. The lower the p-value, the better the results are. P-values directly represent the probability of results being obtained by a chance. Hence, p-value of 0.01 can be represented as that there is 1 percent probability of results from the research happened by chance.

4.6 Research model

In order to measure stock price sensitivity on our factor, the first step of the analysis is constructing the factor. After the factor is obtained, portfolio sorts are performed. We need to estimate betas for each i representing a car manufacturer from the daily stock prices data set. A rolling window for these estimations is 2 months and the beta will be estimated on daily basis. The beta of interest is $\beta(EV(d))_i$ from the following regression:

$$R_{i,t} = \beta_{0,i} + \beta_i^{MKT} * MKT_t + \beta(EV(d))_i * EV(d)_t + \epsilon_{i,t}$$

$R_{i,t}$ is the excess return of the i-th car manufacturer on day t, MKT_t is the excess return on the market portfolio obtained from the Kenneth R. Frenchâ€™s data library on day t and $EV(d)_t$ is the electric-vehicles sales specific factor created earlier based on number of EVs sold divided by the total amount of cars sold for a respective time frame. As in Cremers *et al.* (2015) and Ang *et al.* (2006), there is not need to include any other variables than the market risk premium MKT in order to reduce noise.

In the next step, manufacturers are sorted on monthly basis into three equally-balances portfolios with ratios 6:7:6 based the estimate of $\beta(EV(d))_i$ on the first day of each month. Monthly returns of portfolios as a proportional sum of average returns or each company included in the portfolio are then computed. These monthly risk-adjusted returns of our 3 portfolios are the α of

Fama-French three factor model, representing the premium (see table 1). Also portfolio betas with respect to our new factor and Fama-French three factor values are reported. The model is estimated with an ordinary least squares regression.

Chapter 5

Results and Discussion

5.1 Title of Section One

Results for our portfolios sorted on β^{EV} are reported in the following table. The $R_p represents average monthly returns.$

Portfolio	R_p	α^{FF}	β^{EV}	β^{MKT}	β^{SMB}	β^{HML}
1 High β^{EV}	-0.093	9.446	-0.005	-0.001	0.010	-0.001
2	-0.085	-3.583	0.022	0.005	0.012	0.001
3 low β^{EV}	-0.064	6.613	0.079	-0.002	0.005	0.002
3 - 1	0.029	-2.883	0.084	-0.001	-0.005	0.003

The R_p represents average monthly returns of portfolios.

The difference between the first and the third portfolio alphas is the portfolio strategy premium, which is negative but linear across out sorted portfolios. Base on our empirical results we can conclude there is a monotonic relationship between asset sensitivity on electric vehicles adoption and its returns.

t-values of our premiums are respectively $3.16e^{-5}$, $4.05e^{-5}$ and 0.00328.

Based on our empirical analysis results we can provide an evidence on the pricing of electric vehicles adoption risk. The portfolio sorts method confirms that stocks with a higher sensitivity to electric vehicles adoption risk earn lower returns, compared to stocks with lower sensitivity to electric vehicles adoption.

Since the objective of portfolio sorts is discovery of whether expected returns are related to a certain characteristic, we can confirm that there is a monotone relationship between expected returns and the EV adoption factor.

Chapter 6

Conclusion

Electric vehicles and an overall ecological consciousness adoptions are currently very popular subjects to analyze. The author decided to contribute with his piece of work for the purpose of expanding the empirical research on electric mobility. The main objective of this thesis is to observe an influence on electric vehicles adoption of on stock portfolio performance.

The thesis analyzed the impact of asset sensitivity on a factor of EV adoption on asset returns using the factor analysis. After sorting assets into 3 portfolios on their sensitivity towards the EV factor, monthly returns for each portfolio were calculate. The excess returns, obtained from portfolio returns and market risk free factors, were regressed with portfolios excess returns on the left side, together with alphas, EV factor and three factors from the Fama-French three factor model on the right side.

Obtained results provide an empirical evidence concluding that there is a statistically significant monotonic relationship between asset sensitivity on our EV adoption factor and and its returns. The method of portfolio sorts also confirms that that stocks with higher sensitivity to EV adoption factor earn lower returns.

The objective of this thesis was to analyze to what extent does the factor of electric vehicles adoption explain stock returns of automotive companies. A data set consisting daily data on stock prices of 17 car manufacturers along with U.S. monthly sales data since 2017 were examined to identify an impact of electric vehicles adoption on their stock prices returns using a method of portfolio sorts and Fama-French three factors model. Based on results and tests of each sorted portfolio it is possible conclude that we failed to reject the null hypothesis and therefore there is no statistically significant effect of EVs adoption on stock returns of constructed portfolios.

Since we were using the factor model method, by subtraction of sorted portfolio with highest beta from portfolio with lowest beta, we received an investment strategy premium being 0.029. This represents a premium. Since factors can be interpreted as indicators of underlying concepts, we can assume that the premium represents preferences for more ecological solutions.

The thesis contains a discussion on what is the actual ecological value of electric vehicles compared vehicles with an internal combustion engine, using fossil fuels to generate its power. The difference between these two groups is that possibility of not being entirely dependent on fossil fuels, which is an ecological premium cars with internal combustion engines do not possess. Our empirical analysis shows that more sustainable alternatives to regular combustion engines are valued by investors as well.

Assuming the EV adoption factor describes an underlying patter of ecological consciousness, the analysis provides an evidence of that investments in more environmentally friendly solutions result in the long term in higher returns.

If we were to discuss a possible explanation for such behaviour, meaning why investing in more ecologically friendly solutions yield higher returns, we could argument in a similar way as FAMA & FRENCH (1992) in their analysis of why small companies and companies with high book-to-market ratios experience higher returns, we would need to include the risk factor in our assumptions. The result would therefore mean that companies more sensitive towards less environmentally harmful solutions are somehow expected to be more risky.

Apparently, it might be important for investors to apprehend the value initiatives pursuing an environment conservation and a climate change prevention. Substitution of fossil fuel powered combustion engines with alternatives using electricity from power grid to generate power are one way of lowering the impact of human consumption on the environment.

The following research might for example contribute by estimating the same model on factors created based on a different data set, for example based on data from Europe instead of United States. Not only the data set can be obtained from different resources but also the time frame might be longer. Another possibility of how to contribute might be to estimate data with other models, such as the Fama-French model with five factors instead of three or comparing results from both Fama-French models and the CAPM.

It is worth mentioning that even though vehicles using electric engines and are being defined as electric vehicles due to the fact that they can be recharged from an electricity grid (Proff & Kilian 2012) may seem the be the last and final step in the evolution of human mobility, it would be naive to assume that there will not be any ancestor replacing electric vehicles in the future. Even though there is no infrastructure developed yet and only units of model types have been introduced, the author assumes that with non-zero probability another work focusing on hydrogen cars instead of electric ones, for example, might be conducted.

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Appendix A

Title of Appendix A

Appendix B

Data and code availability

The author hereby declares that all source data sets and code scripts are available upon request.