Master Thesis

Google Trends as Complementary Tool for New Car Sales Forecasting: A Cross-Country Comparison along the Customer Journey.

M.Sc Business Administration

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Abstract

Purpose

The automotive industry is faced with increased demand volatility but still relies on outdated forecasting approaches. The thesis aims to investigate differences in the explanatory power of internet searches to predict new car sales in Germany and the United States with the tool Google Trends. The car buying process is examined and the effect of implementing a time lag within the dataset is assessed to increase the value of internet data. The customer decision journey towards buying a new car illustrates the time lag as the time between the online search for information and the final car purchase decision.

Methodology

Several linear regression models were estimated to investigate the relationship between Google Search queries and new car sales data.

Findings

The study found a significant and positive relationship between internet searches for car models and the car model sales data in both countries with an accuracy of up to 68.5%. The implementation of a time lag highly improved the validity and the accuracy of prediction models that include internet data and opens up new research possibilities. The thesis stresses the value and the necessity to adjust search query data to predict economic variables but raises the awareness of researchers and practitioners not to rely blindly on internet data. The outcomes suggest that the length of the customer journey depends on the car model, the price and is influenced by the national culture.

Academic Contributions

The thesis contributes to the Google Trends literature by examining differences in the prediction accuracy of search queries across countries for the first time and by improving prediction models that include internet data.

Practical Contributions

The results encourage decision-makers in the automotive industry to use tailored search engine data as a possibility to observe people´s interests for particular car models and to enhance new car sales forecasting and demand planning across countries.

Keywords: Forecasting, Predictions, Car Sales, Time Lag, Google Trends, Customer Journey, Cross-Country Comparison, National Culture

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1. Introduction

The first chapter illustrates the importance of the study and embeds the thesis into a context. The research goal, the research question and the underlying theoretical concepts are presented. The academic and practical contributions are highlighted, and the subsequent proceeding of the research is outlined at the end of this chapter.

1.1 Problem Statement

The decision-making process of a company is influenced by the suitability of its forecasting methods since it decreases the dependency on chance and serves as a scientific way to cope with external events (Wheelwright, Makridakis & Hyndman, 1998). Car manufacturers are forced to prepare for the future and to perform demand planning for a variety of car models and countries in a highly dynamic environment (Dharmani, Anand & Demirici, 2015). The efficiency of demand planning across countries causes major problems because tailored approaches are required to handle the diversity of the data which affects the performance of the entire firm (Dharmani et al., 2015). The automotive industry is also characterised by fast changing customer needs reflected in the volatility of demand patterns that serve as a further threat to predict customer requirements in the future (Wyman, 2013; Dharmani et al., 2015). Dharmani et al. (2015) stress the value of new statistical forecasting tools to enhance the capacity planning and the understanding of the entire market. The value of improved forecasts is emphasised by the Institute of Business Forecasting and Planning (2005) because a decrease of the forecast error by just one percentage point lead to an average saving of 3.52$ million per year in their sample. Nevertheless, most car manufacturers still rely on traditional and "home-grown" forecasting tools which are not able to manage the increasing complexity (Dharmani et al., 2015, p.9).

The car purchase decision is shaped by extensive upfront information search of the customer, and several factors are playing a crucial role in the buying process including the underlying national culture (Ernst & Young, 2015; De Mooij, 2010). The way how people walk through the different stages of the customer journey also depends on the level of customer's involvement and predominantly ***starts online*** in the recent years (Kotler & Keller, 2012; Ernst & Young, 2015). However, multiple sources such as personal contacts or professional dealerships are mostly considered before the final buying decision is made (Ernst & Young, 2015; Deloitte, 2014). Thus, Lassen, Madsen & Vatrapu (2014) draw attention to the existence of a certain ***time lag*** between the attention for a product on the Internet and the purchase decision of the customer which needs to be considered in the prediction of sales.

Artola, Pinto & de Pedraza Garcia (2015) reveal that the popularity of the Internet dramatically changed the way how traditional activities are performed including the way how financial transactions are made as well as the process of buying products online. Thus, Reijden & Koppius (2010) emphasise that a ubiquitous amount of data is generated since all of these endeavours leave traces on the web that result in an enormous potential to observe customer´s interests. Ernst & Young (2015) found that consumers invest more time for their information search online before they buy a car in comparison to any other product. Even so, the purchase decision itself is most commonly made in the store (Verhoef, 2007). Hence, the assumption of Ettredge, Gerdes & Karuga (2005) that people's interests are reflected in their online behaviour and in the keywords they submit to search engines has already been confirmed via several web search prediction papers. Choi & Varian (2009a) improved the prediction accuracy in a variety of application fields by including web data into their models. Nevertheless, internet data is rarely used in the sales forecasting context that might result from the reliability and validity issues that are associated with big data (Reijden & Koppius, 2010; Couper, 2013). However, the volume and accessibility of web data can serve as a potential solution to cope with the slow developments of the forecasting approaches and support decision-makers to handle the complexity as well as the dynamic environment in the automotive industry.

1.2 Research Goal and Research Question

A comparison of a search engine based prediction for new car sales in Germany and the U.S. comprises enormous potential. Both countries are responsible for producing about 10 million passenger vehicles each year, and the countries are considered as cultural different which is assumed to be reflected in their consumer habits (OICA, 2015; Hofstede, Hofstede & Minkov, 2011). A quantitative research philosophy is used to investigate the relationship between people´s interests for a particular car model and the new car model sales data with several linear regression models and cross-correlation analyses.

The aim of the thesis is to evaluate whether search engine based predictions differ for new car model sales in Germany and the U.S. The tool Google Trends allows to extract customised search query data that are related to a certain time, country as well as predetermined keywords. However, the identification of differences in the explanatory power of internet searches across countries are crucial for the application in the sales forecasting context, but are neglected so far. This research also investigates the ***existence and the value of a time lag*** in search engine data since scholars already verified this phenomenon with Twitter data (Lassen et al., 2014). The time lag is defined as the time between information search for a product on the Internet and the final purchase decision. The implementation of a tailored time lag into the model enables to quantify changes in the prediction accuracy of the model in Germany and the U.S. An increased value of search engine data through the observation of new patterns and relationships potentially increases the performance of sales forecasting on the car model level as well. The practical value of freely available internet data as a complementary tool for predicting economic variables across countries is also critically reviewed. The analysis intends to raise the awareness of researchers and practitioners ***not*** to rely blindly on raw search engine data but also to demonstrate ways to handle reliability and validity issues of internet data. The consideration of a ***theoretical framework*** potentially improves the value of a prediction and allows to identify differences in the lengths of the buying process that are related to the car price, the vehicle segment or the underlying model. Particular attention is given to the national culture and the possible impact on the car purchase decision in Germany and the U.S. with the purpose to derive insights that allow coping with the cross-national demand volatility. The following ***research question and sub-questions*** will be answered during the subsequent study:

RQ: How does a Search Engine based Prediction differ across Countries for New Car Model Sales?

SQ1: To what extent are Google Trends volumes an accurate predictor of new car model sales?

SQ2: How does the prediction accuracy of new car model sales differ in Germany and the U.S?

SQ3: Does the implementation of a time lag increase the predictability of new car sales?

SQ4: To what extent does a theoretical framework increase the value and understanding of internet-based predictions?

SQ5: Does the length of the average time lag differ between low-priced and high-priced cars?

SQ6: Does the length of the average time lag differ across vehicle segments?

SQ7: To what extent is the national culture reflected in the average time lag in Germany and the U.S?

Three theoretical concepts are introduced to answer the research question and subquestions. Firstly, the different stages that a potential customer goes through are described in three different models. Secondly, Hofstede´s Cultural Dimensions depict the cultural differences between Germany and the U.S. and demonstrate how the national culture is reflected in the consumption behaviour. Lastly, the application fields of search engine based predictions are illustrated to highlight the recent achievements of the research stream. A detailed description of the tool Google Trends provides insights into the data generation, the data collection process and increases the understanding of the analysis. A distinction between predictions and forecasting exposes the terminology used in this research and reveals improvement potentials in predictive analytics from a theoretical point of view.

1.3 Academic and Practical Contributions

This work emphasises the consideration of a ***theoretical framework*** in addition to ***a statistical model*** for predictions to derive beneficial results. The examination of the customer journey and the national culture in addition to the Google Trends analysis create a link between three research streams. The marketing research stream, the cross-cultural research, and the Google Trends literature which unfolds new research possibilities. The thesis contributes to the prediction literature by improving the ***validity*** as well as the ***accuracy*** of prediction models that include internet data. The value of raw and unprocessed search engine data is questioned, and this work enhances researcher´s attention to adjustments in the dataset to reduce the impact of random observations. The study investigates cross-national differences in the properties of the new tool Google Trends for the first time which extends the Google Trends literature. This contribution opens up the potential for further analyses that ***explain the mechanisms behind the identified differences***. The study contributes to the Google Trends literature by investigating the value of search query predictions on the product-level which results in an enhanced applicability in the forecasting context as well. By improving the explanatory power of search queries, this work provides sales forecasting scholars with an advanced variable to reduce the forecasting error in the future. The recognition of a time lag between the generation of internet data and the occurrence in the sales data goes beyond the search engine data research and also encourages social media researchers to be aware of this phenomenon. The benefits and limitations of internet data for academic purposes are compared to a traditional survey which allows researchers to assess the appropriateness of such an analysis. The study proposes guidelines how to increase the value, the reliability and the validity of Google Trends data to improve the prediction accuracy of economic variables in the following studies.

This work provides decision-makers in the automotive industry with a tool that is evaluated in its predictability across countries and therefore reduces the dependency on traditional and outdated forecasting approaches. The Google Trends analysis can be used as a ***complementary and innovative instrument*** to improve new car model demand planning by including up-to-date and tailored search engine data into a forecasting model. The identified patterns within the internet data are narrowed to particular car models as well as countries and serve as an additional variable to justify changes in the capacity planning of a firm. The prediction horizon depends on the lead time that a customer needs to search for information before the final purchase decision is made. The usage of adjusted search engine data to derive insights into customers interests is capable of creating a ***competitive advantage*** until competitors recognise the inherent value of internet data as well. Nevertheless, the comparison of a search engine based prediction between Germany and the U.S. also enables decision-makers to evaluate for which country or particular car model such an analysis is ***less beneficial and less valuable.*** The results support the estimation of customer´s demand on a daily basis that potentially lead to substantial savings for the firm and serves as a way to manage the demand volatility (Moon, Mentzer & Smith, 2003). Improved forecasts for particular car models also strengthen the position of car manufacturers in negotiations with its suppliers as Dharmani et al. (2015) point out that suppliers increase their prices up to 3 % depending on the accuracy of customer´s capacity planning. The classification of the car models into Small-size/ Mid-size/ and SUV-luxury vehicle segments further sheds light on the differences of the length of the car buying process. From a car manufacturers marketing perspective, the link to the customer journey increases the understanding of their customers in Germany and the U.S. The observation of people´s interests can be used for tailored marketing activities to reach the customers in the moments that are most influential on their buying decisions (McKinsey & Company, 2013). The consideration of the national culture raises practitioners awareness to keep the versatile nature of a car purchase decision in mind and adds further substance for marketing campaigns. The Google Trends analysis is applicable to the entire car model portfolio as well as to different countries by conducting only minor changes in the Google Trends data request. This work encourages decision-makers beyond the automotive industry to consider the benefits but also limitations of the vast amount of data that is generated on the Internet.

1.4 Outline of the Thesis

The thesis is divided into ***six chapters*** to answer the research question by providing the relevant theoretical concepts as well as the measurement methodology. The literature review in ***Chapter 2*** introduces different approaches to the buying decision model, the influence of cultural dimensions in Germany and the U.S. on consumption behaviour, and recent application fields of Google Trends for predictions. The theoretical framework is followed by a detailed description of the tool Google Trends in ***Chapter 3*** and draws attention to reliability and validity concerns once internet data is used for an analysis in comparison to a traditional survey. ***Chapter 4*** presents the research design and the conceptual model that comprises the stated hypotheses of the thesis. The research design also provides the data collection process, the scope of the study as well as a description of the measurement. ***Chapter 5*** illustrates the results of the analysis by testing the hypotheses and provides further explanations for the outcome. ***Chapter 6*** discusses the key findings and highlights future research possibilities and the limitations of this study.

2. Theoretical Framework

The Chapter introduces the theoretical construct of the thesis and explains how the literature review was conducted for the identification of relevant gaps. The AIDA model, the customer journey and Kotler´s Five-Stage Model are presented to improve the understanding of different buying decision models. The section is followed by the influences of national culture on the consumption behaviour and points out the cultural differences between Germany and the U.S. A review of recent Google Trends applications to predict several economic variables as well as the consumption behaviour of internet users concludes the chapter. The last section also comprises background information about the concepts of forecasting and predictions. The differences between both terms are pointed out and critically reviewed. Furthermore, the impact of human judgement on forecasting and predictions is illustrated as a Google Trends analysis is supervised by its users.

2.1 Systematic Literature Review

The strategy of the literature review is crucial and affects the outcome of the entire research project (Tranfield, Denyer & Smart, 2003). The thesis uses the guidance proposed by Wolfswinkel, Fuertmueller & Wilderom (2013) to ensure that essential articles, books and other sources are identified and properly processed. The five step approach of Wolfswinkel et al. (2013) is preferred in this study to the three-stage review methodology of Tranfield et al. (2003) because a detailed description of the stages is provided and the iterative nature is emphasised. Nevertheless, both concepts are appropriate to conduct a thorough literature review.

Wolfswinkel et al. (2013) state that a thorough literature review is based on the grounded theory method and consists of five steps that are defining the scope (1), searching for relevant literature (2), selecting suitable articles (3), analysing the chosen literature (4) and the presentation (5) of the insights at the end. Firstly, the scope of the literature review was predominantly limited to relevant textbooks and academic articles of the last ten years. The literature review consists of three independent parts but the proposed review method was used for all sections in the same manner except for the entered keywords. As an example for the Google Trends application field review, the articles that deal with social media data such as Facebook are not covered in the literature review to narrow down the scope and the volume of the literature. Secondly, the search for relevant articles required several databases such as EBSCO Research Database, Google Books, Google Scholar as well as Scopus. Google Scholar was mostly consulted since it offers a broad variety of filters such as the year of publishing, the subject area of the article as well as the function to search for publications from predetermined authors. Several keywords and combinations were used to identify the most suitable literature. The predominant keywords were “Google Trends Analysis, “Google Trends Prediction”, “Google Trends” “Customer Journey”, “Buying Decision Process”, “Kotler's Five-Stage Model”, “Hofstede´s Cultural Dimensions”, “Cultural Influences on Consumption”, “Cultural Differences, Germany, United States”, “Forecasting”, “Predictive Analytics”, and “Web Data Predictions”. Based on the search process as well as forward and backward citation of significant articles, most suitable literature was selected as a third step. Fourthly, the abstract, introduction and the conclusion of the articles were read, important papers were analysed and consequently summarised. The analysis was characterised by the identification of relevant information, and comparisons to similar studies. The literature review is based on 62 scientific articles, 14 books, as well as 6 internet sources, and the most significant insights are presented as the last step.

2.2 Buying Decision Models

2.2.1 Five-Stage Model of the Buying Process

Shafi & Madhavaiah (2013) state that several researchers developed a five-stage model to describe consumption behaviour and most of the stages are defined in a similar way. Kotler (2000) illustrates the buying decision process as a ***five-stage model*** including the problem recognition (1) as the first stage, followed by information search (2), the evaluation of alternatives (3), the purchase decision (4) and the postpurchase behaviour (5) as demonstrated in ***Figure 1***.

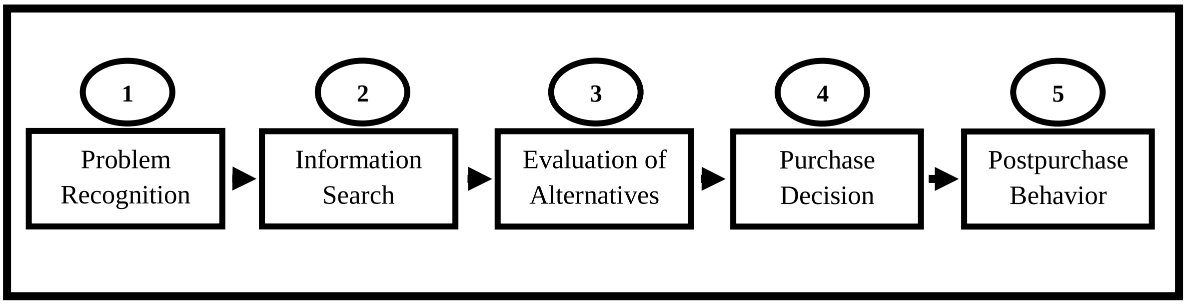

Figure 1: Kotler´s Five-Stage Model (Kotler & Keller, 2012 p. 166)

Kotler (2000) notes that the ***recognition of a problem*** or need is the start of the entire buying process that is triggered by an external (seeing an advertisement e.g.) or internal reason (hunger, thirst e.g.). A need has to pass a certain threshold to result in the recognition of a problem such as the admiration of a friend’s car or the purchase inspirations via television (Kotler & Keller, 2012). The problem is recognised once the consumer found a gap between the desired and the actual state (Shende, 2014). As soon as the problem or need is present, the customer starts with the ***information search*** that can result merely in heightened attention to a certain topic or the active search for information by using the internet, visiting stores or talking to friends (Kotler, 2000). Kolter & Keller (2012) distinguish between four major information sources including personal (such as friends), commercial (such as advertisements), public sources like customer reviews or physically testing the product as an experimental source. The consideration of different information sources results in an increased amount of knowledge and the consumer develops an initial set of brands that fulfils the determined criteria. The step of information search is followed by ***processing the gathered information*** (Kotler, 2000). Kotler & Keller (2012) draw attention to some basic underlying concepts of evaluation despite the fact that the process is non-singular and highly dependent on the customer. The approaches have in common that the client tries to satisfy the primary need by considering the benefits as well as attributes of the identified set of products or brands. The preference for or against certain products is the foundation of the final ***purchase decision*** (Kotler, 2000). Kotler & Keller (2012) state that the buying decision is influenced by the attitudes of others and includes consumer experiences with the product. Unanticipated situational factors also influence the buying decision such as losing the job which is associated with less available financial resources. The ***postpurchase behaviour*** is characterised by satisfaction or dissatisfaction about the decision that results from the upfront expectations and the actual performance of the product (Kotler, 2000). The experiences trigger postpurchase actions such as buying the product again in the future and recommending the product to others (Kotler & Keller, 2012).

Kotler & Keller (2012) note that the way how individuals walk through the different stages depends on the level of the customer’s involvement. Low-involvement goods are related to items that are frequently bought and low-priced such as toothpaste. Customers of low-involvement goods are likely to skip stages in the buying process, going from the recognition of the need straight to the purchase decision without any information search. In contrast, complex and high-priced purchase decisions include high involvement of the customer and the perception of a certain risk (Kotler, 2000). The model is widely adopted for the examination of the relationship between online shopping behaviour and satisfaction (Al Karim, 2013; Pathak, 2014). Deloitte (2014) found that more than 50% of new car buyers spend more than 10 hours for their information search reflected in the lengths of the journey in the car buying process. The five-stage model illustrates the entire process of a buying decision that starts before the purchase is made and goes beyond the actual purchase decision (Pathak, 2014). The walk through the buying process is affected by social, personal, psychological and cultural factors (Kotler & Armstrong, 2012). Waheed, Mahasan & Sandhu (2014) note that the purchasing power of the customer also plays a significant role in the buying decision. The purchasing power describes what customers but also companies can afford determined by their money or income and the price of the product. Hence, the demand for a discounted product potentially declines because the financial situation of the customer decreases to a greater extent. The linear illustration needs additional adjustments to emphasise the iterative nature of the process and the possibility to skip some stages. Furthermore, the problem recognition does not have to be the starting point of the journey as some products are just bought for fun and without the recognition of a certain need. A further limitation can be seen in the sharp illustration of the different stages because of the dynamic transitions between them.

2.2.2 The Customer Journey

Strong (1925) states that E. St. Elmo Lewis was the first in 1898 who emphasised different stages of the customer´s mind that a potential consumer has to pass through before a buying decision is made. The idea was later published and is considered as the foundation of the well-known ***AIDA model***

(Ghirvu, 2013; Hudson, Wang & Gil, 2011). As illustrated in ***Figure 2*** the initial letters refer to the different stages starting with the attraction of ***attention*** (1), the maintenance of ***interest*** (2) the creation of ***desire*** (3) followed by the final stage where the customer takes ***action*** by purchasing the product or service (4) (Lancaster & Withey, 2006). The AIDA model is considered as a relevant hierarchy-of-effects model that points out the way a buyer follows from the unawareness of a particular brand towards the customer-driven action stage as well as the purchase of the former unknown brand (Ghirvu, 2013). The AIDA model highlights the customer´s involvement reflected in the amount of time as well as resources devoted to acquiring the desired product (Ghirvu, 2013). The model is still useful, but researchers share the opinion that the approach neglects the surrounding factors of a buying process (Lancaster & Withey, 2006). The AIDA model is a very simple approach in comparison to Kotler´s Five-Stage Model that does not include any postpurchase behaviour of the consumer. The model takes the perspective of the company into account and describes how the awareness of the own brand can potentially be improved. Therefore it is of practical importance from the companies' point of view. Only the last stage of the AIDA model is characterised by action of the customer in comparison to the great involvement of the customer through all stages described by Kotler (2000).

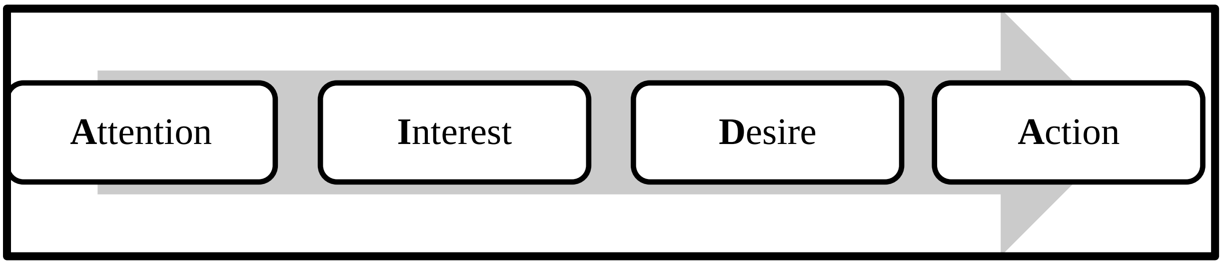

Figure 2: The AIDA Model (Lancaster & Withey, 2006)

The customer journey was traditionally a marketing concept understood as a funnel including a huge number of alternatives at the beginning of the process that are reduced by marketing activities along the funnel towards the actual buying decision (Court, Elzinga, Mulder & Vetvik, 2009). However, the broad product choices, the availability of different information sources as well as social media platforms, call for a less linear and more customer-driven approach that is termed ***customer decision journey*** by Court et al. (2009). Norton & Pine (2013) define the customer journey as "the sequence of events – whether designed or not – that customers go through to learn about, purchase and interact with company offerings – including commodities, goods, services or experiences" (p.12). Court et al. (2009) propose a circular and customer-driven approach that consists of four phases including the initial consideration (1), active evaluation (2), moment of purchase (3) and postpurchase experience (4) as illustrated in ***Figure 3***. The authors based the model on a study of 20.000 purchase decisions of customers from five different industries (Hudson & Thal, 2013).

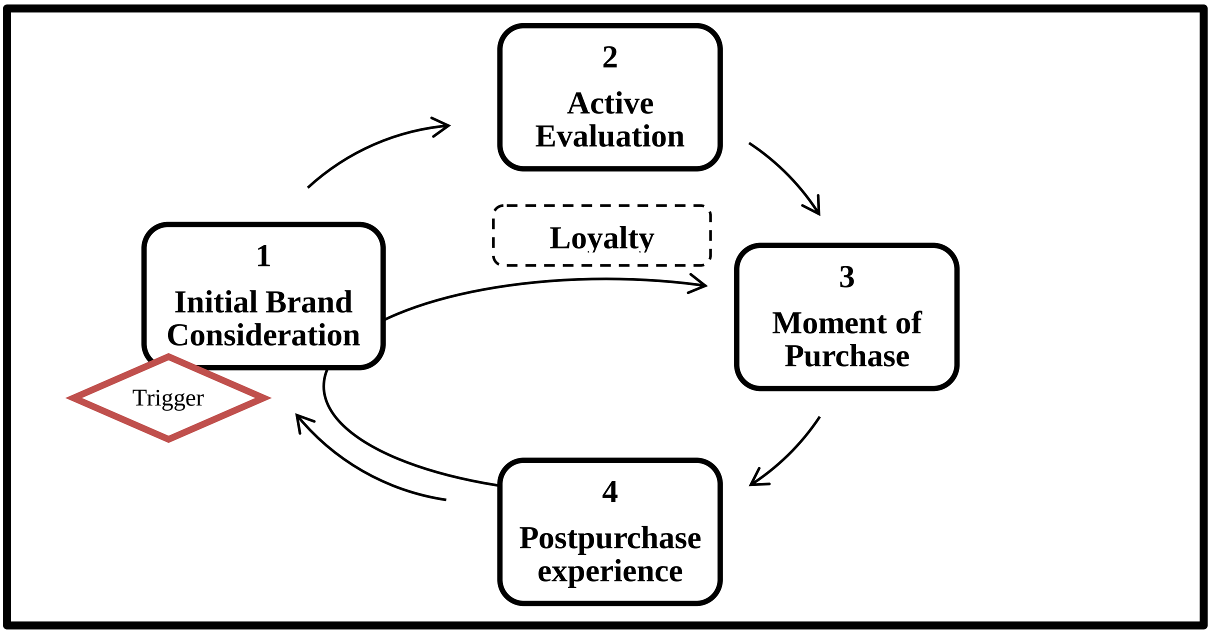

Figure 3: Customer Decision Journey (Based on Court et al., 2009)

Court et al. (2009) state that ***the initial brand consideration*** consists of the set of brands a customer takes into account at the beginning of the journey which can vary across industries. The initial set of a potential car buyer consists of approximately 3.8 brands, and the average customer adds 2.2 brands to their original set during the later stages of the process. ***The evaluation phase*** is highly customer-driven reflected in the volume of online research as well as word-of-mouth. Customers actively search for information to change the number of considered brands. ***The moment of purchase*** and the selection of a certain brand are regarded as the starting point of the ***postpurchase experience*** to inspire loyalty. Court et al. (2009) note that the customer potentially develops brand loyalty that can be reflected in proactive recommendations or repetitive purchases. The model highlights the meaning of being in the initial set of the customer´s considered brands and the importance of investing in consumer-driven marketing. These activities help to reach the customers in the phases where they search for information, reviews and recommendation to evaluate the alternatives (Court et al., 2009). The proposed model changes the traditional form of the buying funnel into a purchasing loop and draws attention to a trigger that explains the initial interest of a customer (Court et al., 2009). In comparison to the AIDA model, the circular model points out the significance of postpurchase experiences and extends the customer journey beyond the buying decision such as Kotler (2000). This model includes aspects such as loyalty and the initial brand consideration and focusses on how to influence the customer decisions. In comparison to Kotler´s Five-Stages, this model changes the linearity of previous buying decision models to a circular approach. Nevertheless, the concepts did not consider any external factors in their models that potentially affect the different stages as well as the length of the process. The customer is also able to leave the buying process at all stages which is not illustrated in the models.

2.3 Cultural Dimensions in Germany and the United States

2.3.1 Cultural Differences and Consumption Behaviour

The consideration of culture to identify consumption patterns is important because cultural values are stable, and most of the consumer behaviour is culture-bound (De Mooij, 2000; De Mooij & Hofstede, 2011). Ackerman & Tellis (2001) found that Chinese consumers touched four times more fruit than Americans in the supermarkets under investigation. Americans shopping time for bananas is only one-fourth compared to the long time that Chinese customers spend for the same shopping decision. The study serves as an indicator for the impact of cultural differences on consumer behaviour despite that their research was limited to food products, the U.S. and China. De Mooij & Hofstede (2010) conclude that the Hofstede Model serves as a valid instrument to evaluate cultural differences in consumer behaviour across countries. A significant amount of studies has already shown that buying motives and differences in product usages are correlated with Hofstede´s Cultural Dimensions including the choice of car type or the usage of the Internet (De Mooij, 2000). The adoption of innovation and the entire decision-making process are confirmed to be related to the underlying culture as well (De Mooij & Hofstede, 2011). De Mooij (2010) verified that the influence of culture and its impact on consumption behaviour increases the wealthier a country gets. The Hofstede Model was developed with the intention to explain the influence of people´s culture and their behaviour in organisations instead of characterising consumer behaviour (De Mooij & Hofstede, 2011; De Mooij, 2010). The literature found significant correlations between the national culture and the consumption behaviour, but it is crucial to consider other influencing factors as well. The financial situation of the consumer or the economic state of the country might force the customers to behave against their national culture.

2.3.2 Hofstede´s Cultural Dimensions

Hofstede (1980a) defines culture as "the collective programming of the human mind that distinguishes the members of one human group from those of another" (p.24). Geert Hofstede developed the Hofstede Model that consists of ***five cultural dimensions***, which is cited as the most frequently applied framework in management as well as marketing research (De Mooij, 2000; Smith et al., 2013). Hofstede distinguishes five dimensions including power distance (1), individualism/collectivism (2), masculinity/femininity (3), uncertainty avoidance (4) and long-/short-term orientation (5) (De Mooij, 2000). The dimensions are indexed from 0 to 100, and the data were derived from IBM employees by using more than 116.000 questionnaires in 72 Countries between 1967 and 1973 (De Mooij & Hofstede, 2002). The Hofstede Model enables comparisons across countries by dimensional scales and provides a mean of quantification as well as correlation to several aspects such as consumption (De Mooij & Hofstede, 2002). Despite the fact that Hofstede obtained the samples of his cultural dimensions in the 1970´s, several authors used the model and dimensions recently (De Mooij &

Hofstede, 2011). The cultural variations serve as an explanation for the relative differences between countries and the behaviour of people as well as organisations (De Mooij, 2000).

Power distance as the first dimension of the cultural model is "the extent to which less powerful members of a society accept the fact that power is distributed unequally" (De Mooij & Hofstede 2002, p. 63). The social status is important for individuals in countries with a high score in power distance, to get the appropriate respect from others (De Mooij & Hofstede, 2011). Hofstede et al. (2010) note that in high power distance countries, the social gap between bosses and subordinates is large and this distance is also preferred and expected by individuals. De Mooij (2000) states that a low score in power distance is related to the desire to look younger. This is assumed to be reflected in the choice of well-designed cars as well.

Individualism "pertains to societies in which the ties between individuals are loose: everyone is expected to look after him- or herself and his or her immediate family" (Hofstede et al., 2010, p. 92). This self-interested group can be seen as the minority in our world (Hofstede et al., 2010). C***ollectivism*** as its opposite "pertains to societies in which people from birth onward are integrated into strong, cohesive in-groups, which throughout people's lifetime continue to protect them in exchange for unquestioning loyalty" (Hofstede et al., 2010, p. 92). Hofstede et al. (2010) state that the consumption patterns of cultures high in individualism are self-supporting compared to a high dependency on others reflected in the consumption patterns of countries high in collectivism.

Masculinity refers to "the extent to which the dominant values in a society are "masculine"- that is assertiveness, the acquisition of money and things, and *not* caring for others, the quality of life, or people (Hofstede, 1980b, p.46). Countries with a high score in ***femininity*** care for each other, the quality of life is important and the status, as well as role differentiation, is less important (De Mooij & Hofstede, 2002). Hofstede et al. (2010) emphasise that women shop for cars ***and*** food in feminine societies compared to countries high in masculinity where men shop for cars and women for food.

Uncertainty avoidance is "the extent to which people feels threatened by uncertainty and ambiguity and try to avoid them" (De Mooij & Hofstede, 2002, p.64). Cultures high in uncertainty avoidance prefer clear roles, formalities, a structured life and the knowledge of experts. On the opposite, countries with low scores in uncertainty avoidance tend to be more innovative as well as curious about new things (De Mooij & Hofstede, 2002; Hofstede et al., 2010). Hofstede et al. (2010) point out that uncertainty avoidant cultures prefer the purchase of a new car instead of a second-hand car.

Long-term orientation refers to the extent to which a country prefers a future-oriented perspective instead of living for the moment (De Mooij & Hofstede, 2002). ***Short-term orientation*** is characterised by personal stability and a historical and conventional point of view (De Mooij & Hofstede, 2011). Hence, long-term oriented countries are described by high saving quotes and the availability of resources for investments compared to a small saving quote and little available resources in short-term oriented countries (Hofstede et al., 2010).

There are several ***other approaches*** to investigate cultural values including the seven-dimensional model developed by Trompenaars (1993) or the ***Tightness-Looseness*** dimension developed by Gelfand et al. (2011). Gelfland et al. (2011) investigated cross-cultural differences with a measure of Tightness-Looseness that is defined as “the overall strengths of social norms and tolerance of deviance” (p.1102). They state that the concept is related to Hofstede´s cultural dimensions but also takes the history and the political environment into account. A high tightness-score emphasises that the country has strong norms and only low tolerance to deviance from these norms. They demonstrated the value of this dimension for cross-cultural differences by comparing 33 countries. Gelfland et al. (2011) point out that the dimension can be seen in everyday situations as well reflected in strong everyday life situations that leave only limited room for appropriate behaviour and weak everyday life situations with a variety of behavioural options. The authors highlight that individuals in tight countries and a lot of strong everyday life situations more precisely evaluate their actions in advance.

Besides the broad acceptance and application of the Hofstede model, ***several limitations*** can be found in the literature. McSweeney (2002) highlights the small sample size and the low amount of questionnaires in the investigated countries. The IBM survey was examined twice (1968, 1973) and only six countries had more than 1000 respondents considering both polls. The surveys conducted in Pakistan ended up with a sample of roughly 100 IBM employees that affects the reliability and validity of the study. Nevertheless, the entire population of a country and the cultural dimensions are defined by these samples. McSweeney (2002) also emphasises that all respondents worked for the same company IBM, but they serve as a representation of the average of an entire nationality. By focussing on IBM employees only, Hofstede excluded several population categories such as the unemployed, full-time students as well as retired people of a country. Steel & Taras (2010) draw attention to the fact that Hofstede´s Dimensions only count for a national average instead of representing individuals. The framework is based on several assumptions including the claim that residents of one country are sharing the same national culture. This equating of national cultures with national states is also pointed out by Baskerville (2003) as a major limitation of the Hofstede model. Nevertheless, the work of Hofstede is highly cited, and correlations between consumption behaviour and the culture were found by several researchers over a long period. Hence it serves as a valid instrument in this thesis to identify cultural differences that are quantified and comparable in Germany and the U.S.

2.3.3 Cultural Differences in Germany and the United States

Germany and the U.S. are considerably similar in macroeconomic figures, but the underlying cultural dimensions are relatively distinct (Smith et al., 2013).

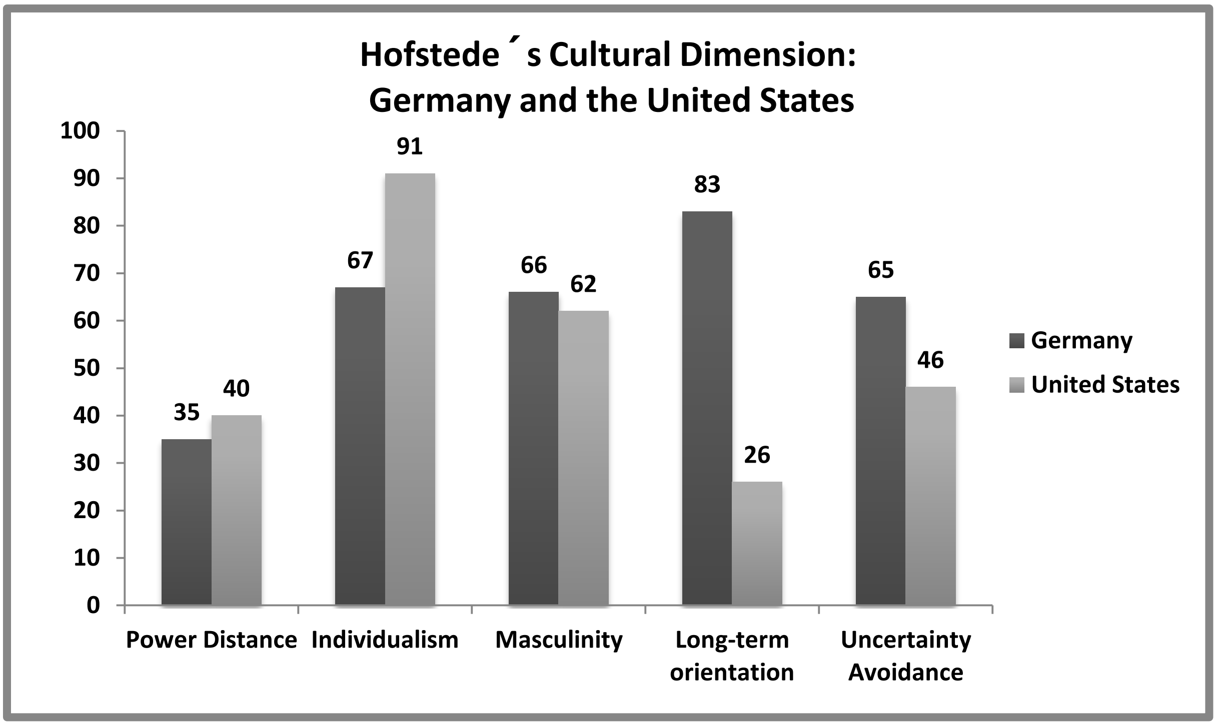

Figure 4: Hofstede´s Cultural Dimensions: Germany and the United States (Hofstede et al., 2010)

Figure 4 illustrates Hofstede´s Cultural Dimensions in Germany and the U.S. with striking differences in long-term orientation, uncertainty avoidance as well as the dimension of individualism. The indices of power distance and masculinity/femininity are almost of equal size. The scores of long-term orientation strike out with an index of 83 for Germany compared to 26 in the U.S. The viewpoint of Germans towards the future is highlighted by the three times higher score in comparison to the low index of Americans. It is assumed that long-term orientated countries are taking care of their resources and hence they are more attracted by advertisements to save money (De Mooij & Hofstede, 2002). De Mooij (2010) found a correlation between long-term orientation as well as individualism and differences in the personal ownership of a car in several countries in Europe.

Germany and the U.S. are different in the dimension of ***uncertainty avoidance***. Uncertainty avoidance explained 85% of preferring new cars instead of second-hand cars with a high significance level ($p< 0.05$) for the year 1991. Yoon (2009) proved that uncertainty avoidant countries have the intention to use less e-commerce with a significance level of ($p< 0.05$-0.01), and therefore he assumes that people in uncertainty avoidant countries may decrease their online shopping behavior.

The U.S. is the most ***individualistic*** culture worldwide with a score of 91 compared to 62 in Germany (De Mooij & Hofstede. 2002). Weighted against the U.S, Germany can be seen as a collectivist country. De Mooij & Hofstede (2010) point out that individualistic countries are searching for fast decisions compared to countries high in collectivism that require the establishment of relationships and trust first. They also state that the cultural dimension of individualism can be used to explain differences in the usage of the internet. De Mooij (2010) states that countries with high scores in individualism are using the Internet more frequently to buy products compared to collectivism countries who prefer face to face contact.

The ***masculinity*** scores of Germany and the U.S. are considerably high (62, 66) with a slightly greater value for Germany. De Mooij (2000) states that the tendency to buy more than one family car is higher in masculine countries. De Mooij (2010) also emphasises that the preference for certain car models and also for car manufacturers is especially related to the combination of the two dimensions of uncertainty avoidance ***and*** masculinity. She found that countries high in uncertainty avoidance (Germany, 65) and masculinity (Germany, 62) prefer technologically excellent, well-designed and safe cars. She associated these attributes to the preference for the German car manufacturers Volkswagen, BMW and Audi. Countries low in uncertainty avoidance (U.S, 46) in combination with a high score in masculinity (U.S, 62) prefer big and powerful cars and are particularly attracted towards the car model SUV (De Mooij, 2010).

Germany and the U.S. hold striking differences in three out of five cultural dimension. Nevertheless, Hofstede´s Dimension are also subject of critique and therefore the ***Tightness-Looseness*** dimension of Gefland et al. (2011) is considered to back the existence of cultural differences in Germany and the U.S. Gelfland et al. (2011) found significant differences in the tightness-score between Germany 7 (average of West Germany 6.5 and East Germany 7.5) and the U.S. with a score of 5.1. The score of 5.1 in the U.S. is also below the total average of 6.5 (entire sample) and points to the loose culture in the U.S. Hence, it is assumed that the time spent for evaluation of alternatives is also reflected in the long purchase decision of a car in Germany since huge investments are carefully evaluated.

2.4 Google Trends Predictions and Forecasting

2.4.1 Predictions and Forecasting

Explanations and Predictions

Shmueli (2010) states that the application of statistical models can be used with the purpose for predictions. Gregor (2006) points out that predictions say “what will be but not why” and that a prediction is possible without knowing the reasons behind (p. 625). The statement of Gregor (2006) does not include any theoretical construct that supports the outcome of a prediction. She states that the appearance of a future event is likely to happen in prediction theory if particular preconditions hold in the future. Siegel (2013) also notes that predictions do not have to be accurate to be valuable for companies as predictions outperform any assumptions and support decisions with empirical data. Shmueli (2010) defines predictive modeling “as the process of applying statistical model or data mining algorithm to data for the purpose of predicting new or future observations” (p.291). According to her definition, any method that produces predictions can be seen as a predictive model and the term new observations also include observations that were not obvious within the original dataset in addition to the observations of future events (Shmueli, 2010; Shmueli & Koppius, 2010). Shmueli (2010) also emphasises the necessity of differentiating ***explanations*** from ***predictions*** by stating that the former aims to explain causally and the latter to empirically predict as well as to evaluate the predictive performance. She defines explanatory modelling as “ the application of statistical models to data for testing a causal hypothesis about theoretical constructs” (p. 291). The paper of Shmueli (2010) emphasises the importance of a theoretical construct for explanations which describes the phenomenon under investigation. In contrast, she states that predictions are based on data, rely on statistical models and neglect the surrounding theoretical concepts. She notes that predictions are also able to look into the future, and therefore the definition includes the prediction of future values. Thus, explanations are based on ***theory*** and predictions on ***data***. However, the distinction of Shmueli (2010) between both concepts is too sharp, and predictions without a theoretical construct limit the practical value for decision makers. ***The understanding of predictions in this thesis is as follows***: The recognition of surrounding ***theories*** is also crucial for predictions in addition to the observation of ***new*** or ***future*** events within the data or outside the data. Hence, the thesis adds that a causal theory is necessary for predictions to explain the predictive performance of a statistical model and to decrease the risk of discovering observations or relationships only by chance.

Forecasting and Predictions

Siegel (2013) notes that ***forecasting*** “makes aggregate predictions on a macroscopic level” such as estimating the exact number of next months ice-cream sales in Nebraska (p. 16). He defines forecasting as “an estimate of the probabilities of the possibilities for a key variable at a future point in time” (p. 4). A possible outcome of a forecast is that car sales grow with 65% chance, compared to 10% chance that no growth occurs and 15% chance of the appearance of a declining sales trend. Thus, the provision of ***several*** future events that are associated with probabilities can be seen as a difference between forecasting and predicting. A time-series forecast is considered as more complex than a prediction by taking more variables, seasonality, autocorrelations as well as smoothing techniques into account (Knaub, 2015). Forecasting can be distinguished based on the time horizon into short-, medium- and long-term forecasts (Mahadevan, 2010). Short-term forecasting relates to a period of 1 to 3 months; medium-term forecasting refers to 12 to 18 months, and long-term forecasting typically relates to a period of 5 to 10 years (Mahadevan, 2010). The literature considers forecasts as more complex than predictions and accurate variables to investigate future observations are essential. A prediction that is justified by a theoretical construct potentially improves the quality of forecasts because the insights that were derived from the predictions can be applied in a forecasting model as well. The literature states that both concepts are useful to identify new observations. Nevertheless, ***the thesis differentiates*** between ***forecasts*** that foretell ***out-of-sample*** events in the ***far*** future and ***predictions*** that are based on data in addition to a supporting theory to observe new or future events that can also be detected ***within*** the sample. However, predictions are also able to look into the future but with a shorter time frame and without the provision of probabilities. Furthermore, a forecast includes several variables and the prediction in the underlying study only includes Google Trends data as the independent variable.The literature review showed that both terms are used interchangeably by many authors despite the emphasised differences.

Shifts in the Forecasting Context

McCarthy, Davis, Golicic & Mentzer (2006) draw attention to the shifts in the forecasting context in the past 20 years through the occurrence of the internet, the globalisation as well as through the increased number of sophisticated forecasting models with and without software support. Nevertheless, companies and managers are often not familiar with these upcoming approaches due to the lack of training and poor commitment of resources which results in unsatisfactory forecasting performances. Rieg (2010) found no increase in the forecast accuracy by analysing sales data over 15 years in the automotive industry. The low developments in forecasting call for new approaches that improve the sales forecast performance. Reijden & Koppius (2010) draw attention to the value of predictions in sales forecasting by including "online product buzz" into the model. Online product buzz refers to the "expression of interest in a product" in online sources such as search engines, blogs or online reviews (p. 2). The predictive accuracy of their models increased up to 28% by taking internet data into account. They encourage the usage of online data for sales forecasting since it allows to listen to the voice of the customer as well as to follow the customers on their trails in the web.

2.4.2 Judgmental Forecasting as a Source of Inaccuracies

The slow developments in sales forecasting resulted in an increased complexity of the forecasting methods without getting the desired improvements in the forecasting error in the past 15 years. Hence, the investigation of potential sources for inaccuracies that go beyond the statistical properties of the models is required. Humans have the possibilities to alter the outcome of the most complex models since incentives exist under certain circumstances. Consequently, every forecasting method involves some judgment (Wright, Lawrence & Collopy, 1996). Human reasoning characterises judgmental forecasting, and judgment is a dominant concern in this context. Armstrong, Green & Graefe (2010) state that judgmental forecasts are often used if inadequate data is available for quantitative approaches or in situations where qualitative information such as expert knowledge is beneficial for the forecast accuracy. They also point out that the statistical and judgmental approaches considerably overlap. Fildes, Goodwin, Lawrence & Nikolopoulos (2009) found that approximately 80% of the investigated companies use statistical forecast software, and the results are adjusted and controlled by their demand planners. The value of such adjustments depends heavily on the company context and the expert or market knowledge of the forecaster. ***Bias*** and ***strategic misrepresentations*** can be seen as sources for inaccurate forecasts.

Optimism ***bias*** refers to the psychological tendency of judging forecast outcomes too optimistically (Naess, Anderson, Nicolaisen & Strand 2015; Armstrong, 1985). Furthermore, the bias of a judge is larger in situations where forecasters are personally involved, and when bias is associated with personal benefits once desirable forecasts are provided to the client (Armstrong, 1985; Naess et al., 2015). Fylvbjerg (2008) states that optimism bias can be decreased with implementing empirical data and by comparing the project with similar ventures. He points out that ***strategic misrepresentation*** is associated with organisational and political pressure. Based on a survey in Scandinavia, Naess et al. (2015) found evidence that incentives for strategic misrepresentation exist in the traffic forecasting context since the forecast results are used to negotiate for funding as well as for rationalising potential expansions of the capacity. Fylvbjerg (2008) found that strategic misrepresentation can be handled by rewarding accurate forecasts and punishing those characterised by inaccuracy. Armstrong, Green & Graefe (2015) encourage managers to hide the purpose of the forecast to get independent results. These sources of inaccuracies call for a more transparent forecasting approach by using simple calculations and additional tools to identify a diverse set of potential outcomes (Naess et al., 2015). Makridakis, Hogarth & Gaba (2010) note that simple models are more useful for predictions than those high in complexity as they ignore some patterns but extrapolate trends instead. Besides bias and strategic misrepresentation, they draw attention to unexpected and unpredictable events as a cause for inaccuracy. People tend to underestimate the likelihood of these rare events by simply defining them as outliers. These sources of inaccuracies can potentially lead to judgmental adjustments of statistical forecasting outcomes. Therefore, several researchers quantified the impact of judgmental adjustments on the forecasting accuracy as well as the distribution of the most common forecast methodologies. Fildes & Goodwin (2007) found that judgment alone is used in 24.5% of the cases, compared to 25% of forecasters that exclusively use statistical methods. The most common approach builds the combination of judgmental adjustments with statistical forecasts (33.1%). An average of judgment and the statistical forecast is used in the remaining (17.7%) of the respondents. They found a median reduction of the forecasting error of 7% once humans adjust statistical forecasts. The tool Google Trends also requires human interaction to extract the Google data and therefore offers potential for errors. Nevertheless, the data extraction can easily be repeated and controlled which reduces the likelihood for misrepresentations.

2.4.3 Google Trends Application Fields

Nowcasting and Forecasting with Google Trends data

The application of internet data ranges from nowcasting (observation of influenza activity e.g.) to forecasting (tourism, unemployment rate e.g.) along with the measurement of issues where traditional approaches reach their limits (Askitas & Zimmermann, 2015). Choi & Varian (2012) state that ***nowcasting*** refers to predicting the present instead of the future. However, they also use simple forecasting models to predict up to 3 weeks ahead (Choi & Varian, 2009a). Askitas & Zimmermann (2015) relate nowcasting to the acquisition of data considerably faster compared to traditional approaches. Castle, Fawcett & Hendry (2009) point out four reasons why nowcasting or “forecasting the current state” is performed and required (p.71). Firstly, nowcasting supports decision-makers in situations that require timely data, and where certain time lags characterise the publication of such figures by statistical agencies. Secondly, the preliminary published data is often a rough estimation itself and therefore subject to later revisions that affect the reliability of the information. Thirdly, the composition of the data potentially differs across periods because some parts of the data are unavailable for a certain time. Fourthly, nowcasting is still useful once the data is fully available since it can serve as an alert system that supports fast decision-making. Nowcasting refers to the prediction of figures that are already in the sample and to perform forecasts up to two months ahead, compared to a 12-24 months period that is associated with forecasting (Carriére-Swallow & Labbé; Fantazzini, 2014). The definition of nowcasting in the Google Trends literature stream is ***different to the definition of predictions.*** Nowcasting relates to predicting the ***present*** in contrast to the definition for predictions that observe ***new*** but also ***future events (***Shmueli, 2010).

Ettredge et al., (2005) are amongst the pioneers in examining the potential of web search data to predict macroeconomic variables. The authors assume that people´s interests, needs, and concerns are reflected in their online behaviour and in the keywords they submit to search engines. Ettredge et al., (2005) analysed the relation between employment-related searches extracted from World Tracker's Top 500 Keyword Report and the official unemployment rates in the U.S. They determined the six keywords "*jobs", "monster.com", "employment", "job listing", "resume" and "job search"* based on the assumption that job seekers use these terms frequently. They found a positive and significant relationship between job-search intensity and unemployment levels. They emphasise the potential of using web-search data to predict economic variables in different contexts. However, they are an exception in the research stream since they perform their analysis with internet data from World Tracker´s Top 500 Keyword Report instead of using data from one search engine (Askitas & Zimmermann, 2015). The database collects keywords across search engines, and the volume is published on a weekly basis (Ettredge et al., 2005).

Predictions of Economic Variables and Private Consumption

Choi & Varian (2009a; 2009b; 2012) predicted near-term variables including ***travel destinations*** as well as motor-vehicle-parts and ***housing sales*** in the U.S. Based on the assumption that Google is used to plan the next holiday trip, an increase in destination-related search queries enabled the prediction of tourism activity. The analysis revealed a significant correlation between the frequency of the search term "*Hong-Kong"* from several countries and the actual visitor arrival statistic. Choi & Varian (2009a) also extracted Google Trends data from the category "*Automotive/Vehicle Brand.".* They included the data for 27 predetermined car makes into a simple regression model for the prediction of U.S. cars and light trucks sales. The car sales data for each investigated model were extracted by "*Automotive Monthly"* and serves as the dependent variable in the regression model. They estimated the model for each of the 27 car brands separately. Choi & Varian (2009a) further investigated the prediction power of Google volumes for house sales and ***several retail sales*** including "*motor vehicles* *and parts*". They used the most recent Google Trends data to make predictions about the sales up to one month ahead. Choi & Google´s Chief Economist Hal Varian are aiming to familiarise readers with Google Trends and to motivate them to perform similar research. The authors are not claiming to predict the future with Google Trends, but the search volume for a particular car in the second week in one month might be useful in predicting the car sales of the same month (Choi & Varian, 2012). Choi & Varian (2009a) found evidence that even simple regression models that include the Google Trends data improve the prediction performance of economic variables up to 20% compared to models without Google Data. They measured the prediction performance of the model by comparing the mean absolute errors of the models that include Google data with the models that exclude the Google variables over the entire period.

Wu & Brynjolfsson (2009) point out the accuracy and simplicity of web search data to predict ***housing market sales***, and prices in the U.S. The implementation of Google search terms into their model reduced the mean absolute error from 0.441 (model without Google Data) to only 0.102. Carriére-Swallow & Labbé (2013) focused on Chile´s market to predict car sales. Despite the low internet penetration rate in Chile, they supported previous findings by indicating the value of a Google Trends analysis in emerging markets as well.

Fantazzini & Toktamysova (2015) contribute to the previous literature by considering economic variables in addition to Google data to propose a set of multivariate models. They tested models that include Google Trends data to forecast long-term sales up to 24 months ahead for the first time. Fantazzini & Toktamysova are pioneers in this context, given that previous studies focused on the forecast (prediction) horizon of less than a few months. They analysed ***new car registrations*** from the Federal Motor Transport Authority (Kraftfahrtbundesamt) in Germany for domestic as well as foreign car producers. They tested the data for seasonality and included economic variables in the models such as the state of the national economy (GDP), the underlying unemployment rate or the petrol price. They found that models including Google data as well as economic variables outperform competing models that did not include economic variables for short and medium-term forecasts. Nevertheless, parsimonious models that include merely car sales and Google search data outperform complex models for long-term forecasts. Parsimonious specifications refer to the integration of simply car sales figures and Google data, whereas the complex models include many economic variables in addition to car sales and Google Trends data.

Askitas & Zimmermann (2009) studied the relationship between Google keywords and ***unemployment rates in*** Germany. They limited the study to four predetermined sets of keywords that they linked with job search activities such as "*unemployment office"* or the name of popular job search engines such as *"Monster".* They found strong correlations between unemployment rates in Germany and Google queries. Many researchers followed Askitas & Zimmermann to predict unemployment levels with internet data in several countries. Choi & Varian (2009b) investigated the unemployment rate in the U.S., Vicente, López-Menéndez & Pérez (2015) in Spain, Suhoy (2009) in Israel and Fondeur &

Karamé (2013) applied similar research to predict the level of French ***youth unemployment***. In the latter case, Google data enhances the prediction accuracy of the youth unemployment rate by decreasing the error term of the model by 17.5%. Baker & Fradkin (2013) investigated the effect of ***unemployment insuranc***e on the amount of job search-related queries in different areas of Texas. The study reveals that job search intensity is twice as high for individuals with 0 to 10 weeks of remaining unemployment insurance in comparison to people with coverage for a longer period.

Predictions of Influenza, Time Perspective, Stock-Market Movements and Desirability Bias

Ginsberg, Mohebbi, Patel, Brammer, Smolinski & Brilliant, (2009) observed the ***activity of influenza*** by using web queries such as "*influenza complication*" or "*Cold/Flu Remedy*" extracted from Google Trends. They found a high correlation between the frequency of predetermined search queries and the actual stationary visits of patients. They state that the findings facilitate the estimation of the current influenza activity levels with a lag of one day. The up-to-date estimations enable health experts to react to seasonal epidemics in advance and to distribute resources such as vaccinations more efficiently (Ginsberg et al., 2009).

Noguchi, Stewart, Olivola, Moat & Preis (2013) applied Google Trends data to measure the ***time-perspective of nations***. They are aiming to identify whether nations with a high GDP are more concerned about the future compared to nations with a low GDP. The authors investigated the extent to which users search the Internet more frequently for events in the future than in the past. They examined in the year 2011 how frequently the term "*2010"* or respectively "*2012*" was entered into the search engine and how these frequencies changed during the year. The study revealed that nations with a high GDP are less concerned about the past and subsequently more focused on the future. This research draws attention to the ability to apply a Google Trends analysis to build psychological constructs and to link it to the economic activity of a nation. They note that the measure of time-perspective is related to Hofstede´s Dimension of long-term orientation with an additional separation between future and past orientation.

Preis, Moat & Stanley (2013) analysed changes in finance-related Google queries to identify ***stock market movements*** and ***early warning signs*** in the U.S. The study draws attention to the trading behaviour and information gathering process of actors. The authors assume that the online information search behaviour acts as a precursor of the final trading decisions. They found that Google Trends data provides insights into the future behaviour of economic actors. Increases in predetermined financial-related keywords function as an early warning sign for stock market falls. They state that the findings are beneficial to develop trading strategies. They assume that investors who are faced with low-priced selling decisions on the financial market are in a state of concern. During this period, they tend to search for more information about the financial market which is reflected in an increased search volume (Preis et al., 2013).

Stephens-Davidowitz (2014) investigated the extent of ***desirability bias*** in Google Trends data. They describe this phenomenon as the tendency of people to hide the truth as they are asked about sensitive topics such as their attitude towards racism. Google searches are significantly less vulnerable to desirability bias than surveys because of the user´s perceived anonymity (Stephens-Davidowitz, 2014). Stephens-Davidowitz (2014) investigated Google Search queries in different parts of the U.S. that contain ***racial expressions***. The study assessed the impact of racial animus on Barack Obama´s 2008 vote share. They calculated a proxy of racism for an area as a percentage of racially-related searches of the overall search volume in the underlying area. In contrast to traditional survey approaches, the study found that racially charged searches are a good predictor for Barack Obama´s underperformance in certain areas. Consequently, Barack Obama lost a substantial amount of votes in areas that are high in their calculated racism proxy compared to previous Democratic presidential candidates. The racial prejudice estimations that use Google Trends data are up to three times greater than survey estimates due to the tendency of people to hide socially unacceptable attitudes.

Google Trends Predictions in Comparison to Traditional Surveys

The assessment of a Google Trends analysis compared to traditional surveys appeared as another research stream in the past (Stephens-Davidowitz & Varian, 2014). Della Penna & Huang (2009) used Google volumes to identify changes in consumer sentiments by investigating differences in online search patterns in the U.S. and Canada. They developed a consumer sentiment index by taking changes in search patterns into account to compare their findings with existing survey-based sentiment indices. The developed consumer sentiment index enabled the prediction of retail sales as well as future consumer spending and has a correlation coefficient of 0.9 with leading survey indices. The implementation of Google data improves the adjusted R^2 up to 24% to forecast consumer spending in comparison to models without the sentiment data from the Internet. Hence, the Google Search-based index performs better to predict consumer spending than the two leading surveys.

Vosen & Schmidt (2009) also compared the forecast performance of a Google Trends analysis for private consumption to well-known survey indices including the Conference Board Confidence Index. Researchers traditionally use surveys to predict private consumption by asking households about their current tendency towards significant investments in the future and their current financial conditions. The authors assume that consumers are searching for products on the Internet that facilitate the prediction of future consumer expenditures. The study reveals that Google Trends outperforms the results of traditional surveys in their predictive performance and hence offers enormous potential to forecast private consumption.

3. Google Trends as a Source of Internet Data

Chapter 3 provides information about Google Trends itself and introduces the benefits and limitations of the new tool in comparison to a traditional survey. Reliability and validity issues of Google Trends data are described and possibilities to cope with the problems of internet data are highlighted. The chapter concludes with an explanation of a regression analysis as a common method to identify correlations between internet data and economic variables.

3.1 The Tool Google Trends

The Internet is an important information source, and billions of queries are entered into search engines each day (Vaughan & Chen, 2015). Google provides different tools that enable researchers to access and use Google data for various application fields (Stephens-Davidowitz & Varian, 2014). The web queries of Google present a "Treasure House for web data mining" because people´s interests and concerns are mirrored (Vaughan & Chen, 2015, p13.) A search query is "a complete, exact sequence of terms issued by a Google Search user" (Ginsberg et al., 2009, p.1014). Google provides a segmentation of the queries into categories such as "*Computer & Electronics*" and the data is available since January 2004 (Wu & Brynjolfsson, 2009). The tool does not publish the absolute number of searches for a particular keyword but normalises the search volume of queries to make search terms comparable across regions (Google, 2015). Therefore, Google divides each data point by the total search volume of the investigated geographic area and the time range (Google, 2015). Stephens-Davidowitz & Varian (2014) note that Google Trends generates the popularity of a keyword by publishing a value from zero to 100. The index of 100 indicates the maximum query share for the predetermined category. Supposing that one data point for a request is indexed with 100 and a second one has an index of 50, the searches for the first data point are twice as big as for the second one. Hence, Google Trends shows the ***relative interest*** of people (Google, 2015). Stephens-Davidowitz & Varian (2014) state that a declining trend for a term in Google Trends does not mean that the absolute number of searches for the keyword also decreases. These results occur because the overall amount of search queries for the determined filters increases over time and the keywords percentage decline. As Google Trends generates the data from a sample, the extracted trend information slightly differs for each request (Stephens-Davidowitz & Varian, 2014). ***Figure 5*** shows the relative popularity of the search term "***Volkswagen***" in Germany and the U.S. for the year 2015. The red line indicates people´s interest in the U.S. in comparison to the blue line for Germany. The interests in Volkswagen are quite similar in Germany and the U.S. with an index between 30 and 40 over the weeks in 2015. In week 19, Germany has a Google Trends index of 39 compared to 4 Google Trends index points less in the U.S (35). Thus, people´s relative interest in Germany is higher for the term "Volkswagen" in comparison to the U.S. in week 19 of the year 2015. What particularly strike are the outliers in the sample around the week 38. Germany generates the maximum index of 100 due to the Volkswagen emission scandal compared to an also high value of 94 in the U.S. at the same time. The scandal raised people's interest about the company Volkswagen that is reflected in the high volume of search queries. The figure points out that Germany accounts for the highest overall search volume for the entire sample reflected in the index of 100 in week 38. Hence the entire request reflects people´s interest in relation to the maximum index generated in week 38 in Germany. Google Trends data is freely available to the public and can be accessed and downloaded at "*https://www.google.com/trends*" (Wu & Brynjolfsson, 2009).

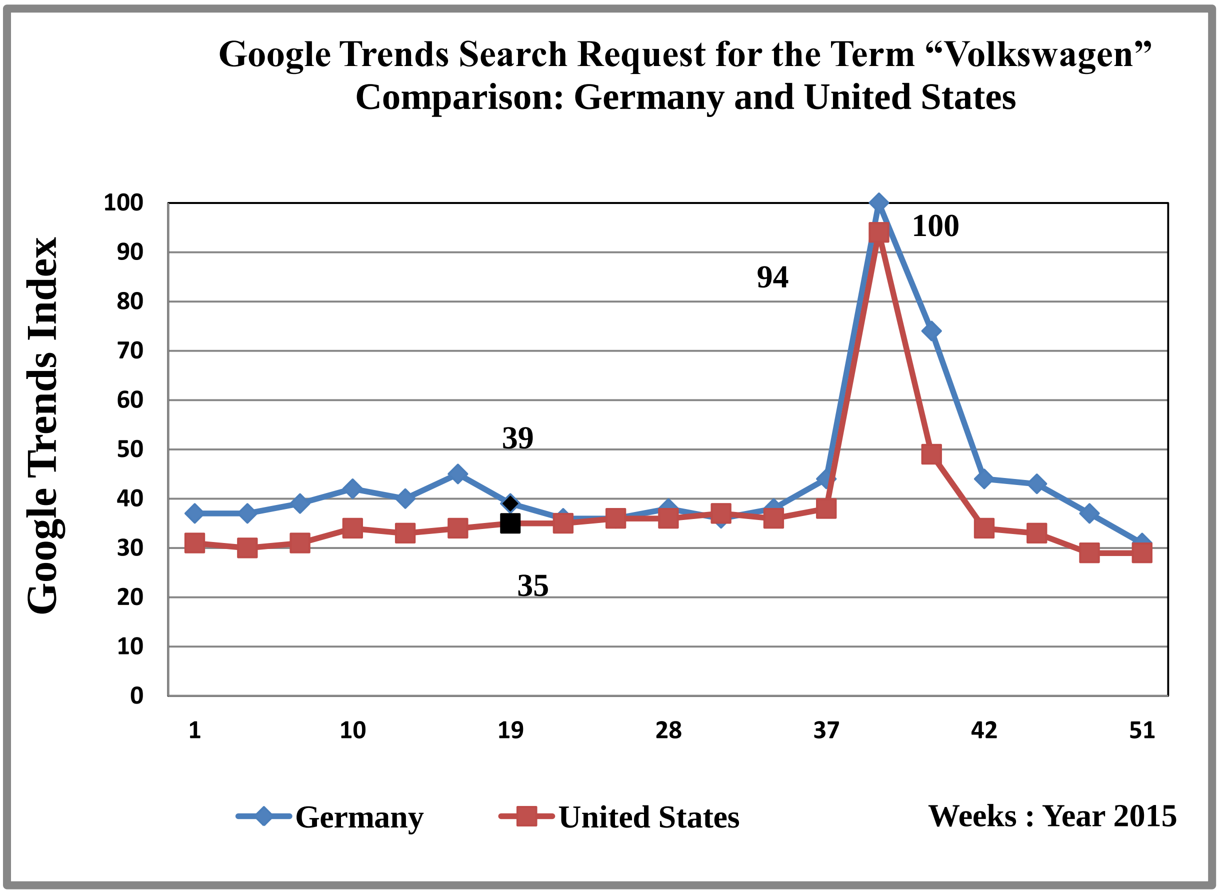

Figure 5: Google Trends Search Request for the Term "Volkswagen"[1]: Germany and the United States

3.2 Reliability and Validity of Google Trends Data

The usage of internet data requires particular attention to the validity and reliability to facilitate that web data truly reflects what the researchers are interested in (Zhu, Wang, Qin & Wu, 2012). Babbie (2015b) points out that a measurement should be valid as well as reliable to ensure its usefulness. However, it seems that little attention was spent to both concepts in the Google Trends literature. According to Rubin & Babbie (2009), reliability is concerned with the amount of random errors in a measurement and whether a repetition of a certain technique results in the same outcome. Therefore, ***reliability*** deals with the consistency of a measurement (Babbie, 2015a). Choi & Varian (2009a) serve as an example to increase the repeatability of their study because they illustrated each step of their measurement and disclosed the necessary information to apply their methodology. Zagheni & Weber (2015) encourage the evaluation of trends or relative changes instead of focusing on one specific date

[1]https://www.google.com/trends/explore#geo=DE,+US&date=1/2015+12m&cmpt=geo&q=%22Volkswagen%22&cat=0-47

in time to demonstrate a reliable picture of the truth due to the high volatility of internet users. Google Trends normalises the data that affects the reliability of the tool (Google, 2015). Baker & Fradkin (2013) decreased this reliability issue by averaging the data from several samples. They extracted the Google Trends data for the same keyword in 4 different weeks to average the samples as well as to reduce the noise of the internet data. Babbie (2015b) states that the consideration of established measures that already proved their appropriateness can be used to improve the research reliability. Hence, several researchers compared the outcomes of their Google Trends analysis with conventional surveys to assess the value of the new tool. Zhu et al. (2012) found no significant differences in the population of internet users compared to non-users that serve as an indicator of the reliability of search queries.

V***alidity*** refers ”to the extent to which an empirical measure adequately reflects the real meaning of the concept under consideration” (Babbie, 2015b, p.148). The validity of a measurement is difficult to proof, but several criteria can be used to evaluate its appropriateness (Babbie, 2015b). Mellon (2014) distinguishes between ***face-***, ***content-,*** and ***criterion-related validity*** to test the usefulness of internet search data. ***Face validity*** refers to the selection of a reasonable set of keywords that seem to have face validity. The keyword “immigrant” contains face validity to measure issues about immigration. Babbie (2015b) states that such a measure is valid “on its face” (p. 149). Askitas & Zimmermann (2009) used the job database “*monster*” as a keyword that ensures face validity to investigate the unemployment rate as it is assumed that job-seekers use these terms more frequently than employed individuals. *C**riterion-related validity***, also known as ***predictive validity*** refers to “the degree to which a measure relates to some external criterion” (Babbie, 2015b, p. 149). The scores of a written drivers test are associated with the driving records of a person that serves as an external criterion to determine the validity of the written results (Babbie, 2015b). Babbie (2015a) adds the dimension of ***construct validity*** that is “based on the logical relationships among variables” as a further validity criterion (p.153). It is assumed that people who are interested in buying a new car in the near future are more likely to search for the particular car model information on the Internet which is reflected in an increase in the search query volume. ***Content validity*** refers to “how much a measure covers the range of meanings included within a concept” (Babbie, 2015a, p. 154). The content validity investigates the appropriateness of the considered internet searches and if the determined keywords measure what they are intended to do (Mellon, 2014). The content validity of Google Search data can be increased by identifying and excluding terms that are not plausibly related to the topic under investigation (Mellon, 2014). Stephens-Davidowitz & Varian (2014) composed a guideline on how to access and use the tool Google Trends to avoid ambiguity (one word with different meanings such as “Apple”) in search terms by carefully choosing categories to get valid data. Zhu et al. (2012) point out the significance of the keyword selection process to ensure the validity of the research. The selection of categories such as “*Automobiles and Vehicles*” and the limitation to only one country increases the content validity by excluding topics that are not related to cars or the country of interest. The usage of internet data is faced with certain reliability and validity issues. Nevertheless, several techniques are available that decrease the impact of these threats and successfully increase the value of Google Trends data.

3.3 Benefits and Limitations of Google Trends in Comparison to a Survey

Google Trends Limitations: Missing Raw Search Volumes and Search Term Coding

Google Trends does not publish the ***raw search volumes*** and the exact number of people that are interested in a particular topic (Reilly, Richey & Taylor, 2012). The data is normalised and reported once the search volume passes a certain threshold. Stephens-Davidowitz & Varian (2014) state that this threshold consists of an absolute but unreported number. Therefore, the investigation of less common issues is not possible and can be seen as one limitation of using Google Trends data. Nevertheless, this limitation can be managed by increasing the scope of the geographical area or the investigated time frame to pass the threshold and to get the desired data. Google Trends data is sensitive to the ***predetermined search terms*** as the extracted results are influenced by little changes of the keywords (Reilly et al., 2012). Stephens-Davidowitz & Varian (2014) note that the query selection is a major challenge to get the desired results since billions of searches are available. Therefore, the researcher's ability to determine representative as well as relevant keywords affects the quality of the internet data. Nevertheless, survey´s are also limited to a certain amount of questions in comparison to the highly flexible Google Trends analysis (Scheitle, 2011). The most commonly used survey for political issues in the U.S. often lack precision, and the results are only published quarterly or even in yearly intervals (Ripberger, 2011). The tool Google Trends stands out because of its high practicality as the search terms can be changed easily, they are available on a daily basis, and the requests can simply be repeated. In contrast, the replication of surveys is subject to errors stemming from the sample or the interviewers since the way how the questions are constructed or the intonation of the interviewer serve as a source of inaccuracies (Groves, 2004)

Google Trends Limitations: Temporal Coding, Non-Representativeness and Non-Stationary Data

The ***temporal coding decision*** influences how the Google Trends data is scaled and normalised as the index calculations are based on the predetermined period (Reilly et al., 2012). The consideration of a further month in the search query request might affect the entire sample resulting in an over- or underrepresentation of a certain effect (Reilly et al., 2012). This issue can also be observed in a traditional survey due to nonobservational as well as coverage errors that potentially impact the value of a survey by missing out important parts of the population (Groves, 2004). Reilly et al. (2012) point out that internet users are ***not representing a random sample***, as the data just tracks the behaviour of people using Google or the Internet at all. Mellon (2014) emphasises that several demographic characteristics and groups are not represented in the composition of Google searchers. Hence, Google Trends research is limited to areas with a high internet penetration rate. Nevertheless, the high and almost similar internet penetration rate of approximately 88% of the total population in Germany and the U.S. in 2016 reduces the non-probability sampling issue of using search query data in these countries (Internet Live Stats, 2016a; 2016b). Zickuhr (2010) investigated the composition of internet users in the U.S. and found that young generations (18-44y) are overrepresented by counting for about 50% of all internet users compared to 11% of all internet users that are older than 63 years in the U.S. The study found that higher income, as well as higher education, increases the likelihood of going online. Mellon (2014) examined if and how the differences in the internet search population and the offline population introduces bias in the dataset. They tested the demographics of several public salience surveys and the demographics of internet users searching for the same topics. They found that demographic differences are unlikely to introduce significant bias in the dataset due to high correlation results. Scheitle (2011) revealed a correlation of 0.92 between the surveys asking about public topics of interest such as the unemployment rate and the average amount of monthly searches for the same issues. Consequently**,** Mellon (2014) draws attention to the small likelihood of bias in web data despite the differences between internet users and non-internet users.

Google Trends data is also ***non-stationary*** because the composition of internet users, as well as the entered queries, are constantly changing (Suhoy, 2009). The investigated relationships are subject to changes and only hold for a limited period and geographical area (Zagheni & Weber, 2015). Stephens-Davidowitz & Varian (2014) note that in 2004 the Internet was commonly used at universities which was also reflected in the high amount of searches including the term “science”. The composition of internet users dramatically changed in recent years and therefore the interest in the word “science” appears to decline. These insights indicate that a Google Trends analysis is less useful for the investigation of long-term trends (Stephens-Davidowitz & Varian, 2014). Couper (2013) draws attention to the value of surveys to investigate long-term trends since surveys are more stable than data generated from the Internet. However, Groves (2004) points out that the recall of past events is a potential source of errors as well and might affect the accuracy of the survey results. Ettredge et al. (2005) recognise the presence of noise in data generated from the Internet. In their prediction of the unemployment rate in the U.S., employed workers that are searching for better jobs can generate noise in the search query data. The job-related searches by employed people are leading to increased online search data, but the unemployment statistic remains unaffected. Scharkow & Vogelgesang (2011) state that the huge amount of queries and its variability over time still serve as a reliable and valid indicator of changes in people´s interest in political issues. Surveys are also the subject of noise that can be introduced by the sample, the interviewer or the measurement approach (Groves, 2004). Search query data merely covers people´s attention to a certain topic, whilst ***neglecting emotions*** as well as other critical dimensions that are better covered across social media platforms (Zhu et al., 2012).

Google Trends Benefits

The search queries cannot be traced down to individuals, a particular location or the IP address that reduces the ***privacy concerns*** that are inherent in internet data (Ginsberg et al., 2009). McLaren & Shanbhogue (2011) note that Google collects the data as a ***by-product*** of a user´s normal activity in comparison to the active respondents in traditional surveys. They also point out that the steady data collection can result in the identification of unforeseen topics in contrast of collecting data for a predetermined set of questions. These benefits of using internet data reduce non-responsiveness and sources of inaccuracies. Internet data also enables researchers to perform requests ***repeatedly*** as well as in a ***cost*** and ***time-saving*** manner (Askitas & Zimmermann, 2015). Stephens-Davidowitz & Varian (2014) point out that Google searches are significantly less vulnerable to desirability bias than surveys because of the user´s perceived anonymity. Google Trends enables researchers to get new insights on topics that are influenced by social desirability (Stephens-Davidowitz, 2014). Scharkow & Vogelgesang (2011) stress that even highly advanced surveys are dependent on the answers that are given by the participants. A further threat to the validity of survey data is owed to the ability of the personnel to influence the participants responses (Zhu et al., 2012). Furthermore, the ***storage*** of Google Trends data is easy since the search queries are created and saved online (Askitas & Zimmerman, 2015). Google Trends has appealing benefits and opens up new research fields but also enables researchers to investigate popular as well as less popular topics from a different angle (Stephens-Davidowitz, 2014). The observation of internet search data provides a new possibility to verify traditional approaches and to support research in complex and changing environments (Askitas & Zimmermann, 2009; Polgreen, Chen, Pennock & Nelson, 2008). Therefore, the availability of internet data, the coverage, and the huge sample size enable Google Trends researchers to focus on the performance of more advanced analysis (Zhu et al., 2012).

Table 1 summarises the Google Trends ***limitations*** and ***benefits*** in comparison to traditional surveys and illustrates how these differences are affecting the validity, reliability as well as generalisability of the methods.What particularly strikes is the fact that the categories in which Google Trends achieve very low results such as the dependence on keywords and the dependence on the search engine user are also problematic once a survey approach is followed. However, a Google Trends analysis stands out by its flexibility to change the keywords, to repeat the analysis as well as to increase or to decrease the sample size immediately. The simplicity of the method and the time and cost saving properties of a Google Trends analysis further highlight the value of this freely available tool for scientific purposes. Nevertheless, it is also important to state that both approaches are not mutually exclusive, and both techniques can benefit from each other.

Google Trends vs. Traditional Survey							
Google Trends Analysis	**Traditional Survey**	**Validity**		**Reliability**		**Generalisability**	
Normalised Data (Single Variable)	Absolute Number (Multiple Variable)	-	+	-	+	-	+
Low Vulnerability to Desirability Bias	High Vulnerability to Desirability Bias	+	-	+	-	+	-
Predetermined Keywords	Predetermined Questions	-	-	-	-	-	-
Short-Term Trends	Short-Term and Long-Term Trends	+	+	+	+	-	+
Dependency: Interent User	Dependency: Respondents	-	-	-	-	-	-
Manipulation of Data (Keyword)	Way of Questionning (Intonation)	-	-	-	-	-	-
Large Sample	Small Sample	+	-	+	-	+	-
Volatility of the Data	Constant Data	-	+	-	+	-	+
Replicable	Hard to Replicate	+	-	+	-	+	-
Practicality and Simplicity of the Method							
Flexible Changes of Setting	Setting hard to Change	+			-		
On-Going Data Collection (Passive)	Collection of the Data (Active)	+			-		
Free, Short-Dated Access to the Data	Time, Labour, Cost-Intensive Data Collection	+			-		

Table 1: Comparison of Google Trends and Traditional Surveys

3.4 Regression Analysis in the Context of Internet Data

The observation and collection of daily, weekly or monthly data over time is very common in several application fields (Cryer & Chan, 2008). A time-series is a "sequence of values or readings ordered by a time parameter" and the application fields are multitude ranging from monthly figures for economic purposes to sociology as well as meteorology e.g. (Granger & Newbold, 1985, p.1). The Google Trends data is also considered as a time-series determined by the geographical area and the time of the entered search query volumes (Choi & Varian, 2012). A time-series analysis aims to understand the reasons for historical patterns of the data series and to forecast future values (Cryer & Chan, 2008). Therefore, a time-series analysis as a quantitative forecasting technique can be applied when historical data is available in a numerical way and under the assumption that the patterns of the past will also occur in the future (Wheelwright et al., 1998). Frechtling (2011) states that a regression analysis is an appropriate method for investigating the correlations of time-series. Guerard (2013) also emphasises that a regression analysis is a helpful statistical technique to estimate parameters, investigate quantitative data as well as to extrapolate trends. The analysis examines a dependent variable (X) and an independent variable (Y). A regression analysis aims to draw a regression line that fits best to the considered data. Yan & Su (2009) note that the simplest linear regression model consists of one independent variable and one dependent variable as outlined below:

$$Y = \mathrm{a} + \mathrm{b}_1\mathrm{X}_1 + \ \mathrm{e}$$

Where:

Y= dependent variable (or forecast variable)

a= the constant

b= the slope of the regression

X= independent variable (explanatory variable)

e= residual (error term)

The model states that the dependent variable *Y* is a linear function of the independent variable *X* with the slope *b* that indicates the rising-rate of the regression line once the dependent variable increases. The best fitting regression line refers to the line that most accurately estimates the relationship between the dependent and the independent variable (Guerard, 2013). The linear regression analysis is based on the assumption that the relationship between the dependent and independent variable is at least approximately linear (Allen, 1997). According to Lawrence, Klimberg & Lawrence, (2009) the ordinary least squares method is considered as the most common estimation to calculate how well the line fits the investigated dataset. The line with the smallest sum of squares of deviations from the actual data points is termed the best fitting line. The difference between the real data point and the estimated value is reflected in the residual or random error *e* (Frechtling, 2011; Yan & Su, 2009). A regression analysis does not forecast the exact values for a given period since it aims to provide estimations (Frechtling, 2011). As soon as a relationship between the variables is identified, the dependent variable such as sales can be predicted or forecasted with the known variable (Smailes & McGrane, 2000). Moreover, regression models are commonly based on certain criteria that verify the value and the extent of how well the model fits the data (Yan & Su, 2009). The correlation coefficient ***R*** measures the direction of the relationship (correlation) ranging from -1 (perfect negative correlation) to +1 (strong positive correlation) (Smailes & McGrane, 2000). The coefficient of determination ***R^2*** describes the extent to which the variance in *Y* is explained by the variable *X* (Lawrence et al., 2009). The significance level *p* indicates whether a relationship is statistically significant with a certain confidence level. A significance level smaller than 0.05 (5%) is associated with a low probability (less than 5%) that the investigated relationship is not true (Wang & Park, 2015).

Several researchers found a strong fit of their model (high *R^2)* with internet data as the independent variable to predict economic figures. Lassen et al. (2014) estimated a linear regression model to predict iPhone sales with the amount of iPhone tweets. The analysis results were close to well-established models developed by investment bankers with the R^2 coefficient of 0.96. The prediction model of Choi & Varian (2012) investigated the relationship between motor vehicle parts sales and the index of Google Trends that results in a coefficient of determination of 0.808. Hence, 80.8% of the changes in the dependent variable motor vehicle parts sales can be explained by changes in the Google Trends index. Asur & Huberman (2010) estimated a linear regression model with twitter data as the independent variable to forecast movie revenues before the actual number is released with significant findings. Based on an excellent predictive performance ($R^2=0.8$) as well as a correlation coefficient R of 90% they pointed out that the attention for a certain movie is also reflected in its future status. Smailes & McGrane (2000) emphasise that the quality of the regression analysis is dependent on the sample size and they recommend the usage of a minimum of 30 data points. A regression analysis that includes more than one independent variable is called a multiple regression. Nevertheless, Armstrong et al. (2010) indicate that complex models are prone to errors, and they motivate the usage of simple models in situations with a high degree of uncertainty. Armstrong & Green (2015) investigated the appropriateness of complex versus simple forecasting models in terms of accuracy. They found that complexity of forecasting models even harm the accuracy by increasing the forecasting error about 27% on average.

Nevertheless, the assumption that patterns from the past also continue in the future is a ***limitation*** of a regression analysis. Inaccurate outcomes can result once the identified patterns do not occur in the future but also in the case of unforeseen events that were not inherent in the historical data. However, Choi & Varian (2012) showed that Google Trends data can be used to decrease the impact of these "turning points" in economic time-series (p. 6). The performance of a regression analysis is also dependent on the sample size, but the availability of historical Google Trends data is short (Choi & Varian, 2012). This limitation might result in missing important patterns that only emerge each decade or even in longer cycles. Consequently, it is not possible to extrapolate trends that are not in the dataset, but the consideration of internet data is useful in the identification of up-to-date signals (Scott & Varian, 2013). Ao (2010) states that a linear regression does not capture seasonal patterns due to the assumption of linearity in the dataset. However, the application of transformation techniques such as the implementation of ***time lags*** into the time-series potentially decreases this limitation of a linear regression analysis.

4. Research Design

Chapter 4 introduces the research design and the conceptual model by implementing the relevant findings from the previous chapters. This section points out the theoretical implications by drawing attention to the research gaps. A detailed description of the hypotheses and how these concepts are related is stated in the research model.

4.1 Research Design and Conceptual Model

The implementation of a time lag is an essential precondition to ***predict*** economic variables since the model otherwise just causally ***explains*** or "predicts the present" (Shmueli, 2010; Choi & Varian, 2009a). ***Kotler´s Five- Stage Model*** builds the theoretical construct of the underlying analysis to justify the observation of the time lag and to improve the understanding of the prediction outcome. It is assumed that the identification of the ***optimal time*** lag for a particular car model improves the prediction performance of the model because new observations within the dataset can be discovered. The optimal time lag refers to the best identified time lag (highest correlation and significance) for a particular car model. Lassen et al. (2014) verified the value of a 20-day lead time to predict iPhone sales based on Twitter data. They used the AIDA model as the underlying theory to describe the implementation of a 20-day period between the customers attention for the iPhone on Twitter and the action stage reflected in the iPhone buying decision. Nevertheless, Kotler´s Five-Stage Model illuminates the customer journey in more detail and is therefore used in the thesis. Hahn, Choi & Lee (2012) state that the purchase decision of a high-involvement item requires more time compared to a low-involvement good. It is assumed that the purchase decision of a car is planned on a longer time horizon in comparison to the 20-day iPhone period and is therefore illustrated in months. Jansen & Schuster (2011) found that most internet searches are entered into the search engine in the research phase and not in the actual purchase decision phase. It might be difficult to determine the current customer stage because phases can be skipped or even repeated (Kotler & Keller, 2012). Nevertheless, knowledge about the current stage is not a necessary condition for the model as each search query is reflected in the Google Trends data. A larger time lag to buy a car does not necessarily mean a higher search volume because the length is also influenced by the usage of other information sources such as the visit of a dealership. As illustrated in ***Figure 6,*** the first three stages of the buying process are reflected in the volume of Google Trends data and the final purchase decision of a customer (online/offline) can be found in the published new car sales data of the underlying model.

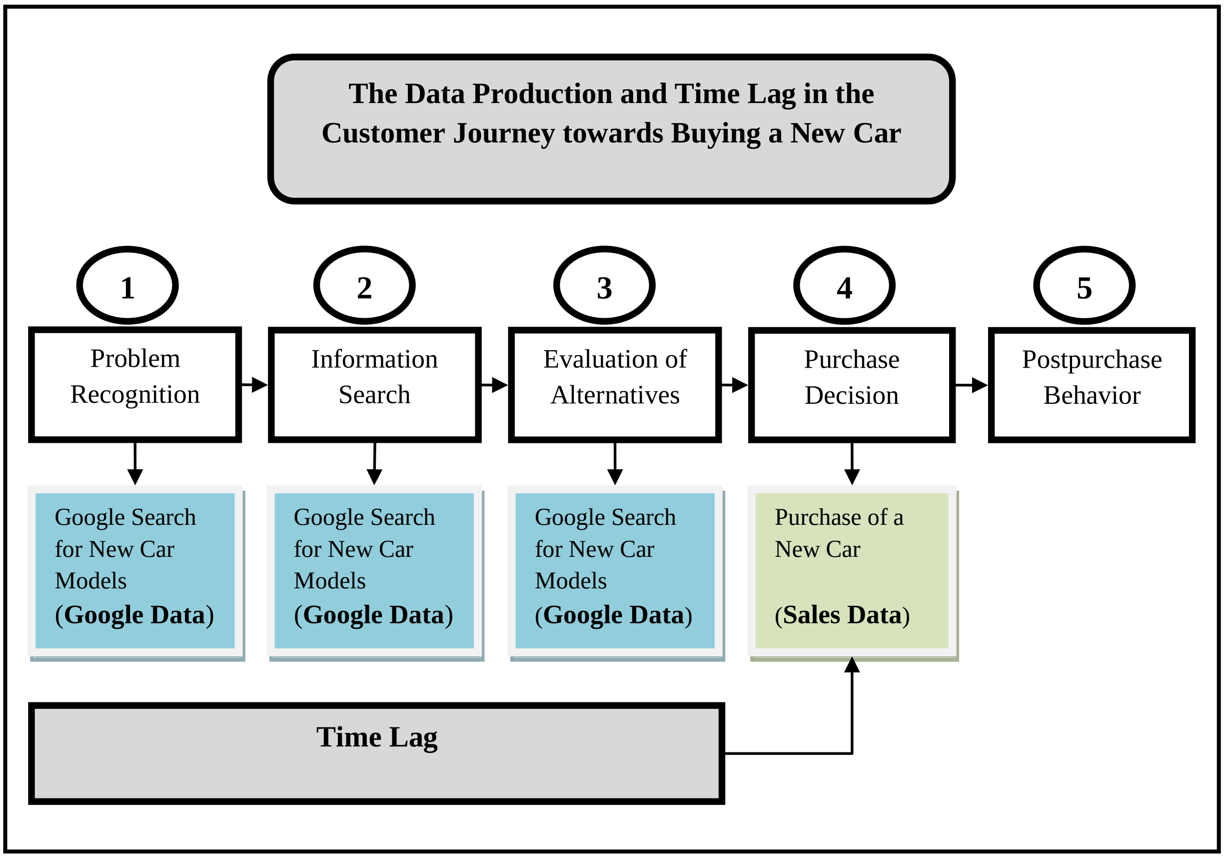

Figure 6: The Time Lag and Data Production within the Customer Journey (Based on Kotler, 2000)

The predictability of new car sales by using Google Trends data is already tested by several researchers (e.g. Fantazzini & Toktamysova, 2015; Choi & Varian, 2009a; Carriére-Swallow & Labbé, 2013). These studies did not provide any theoretical explanations for their findings, and no modifications of the internet data were made despite adjustments for seasonality to increase the performance of the model. The contributions of the thesis are manifold by selecting focused keywords, creating a link to the customer journey, identifying and implementing a time lag to improve the prediction accuracy of the model and by comparing the value of a Google Trends analysis across countries, car models and cultures.

Recent Google Trends analyses for car sales used keywords that include simply the name of the car brand such as "Toyota" instead of the particular car model or further specifications (Fantazzini & Toktamysova, 2015; Choi & Varian, 2009a; Carriére-Swallow & Labbé, 2013). The keywords are assumed to be influenced by individuals searching for news about the company and a link to a car model cannot be drawn. The particular ***car model*** name serves as the search engine keyword in this study to reduce the noise of internet data. Based on the assumption that the amount of internet search queries for a car model is also reflected in the new car model sales data, the first hypothesis serves as a verification of previous car sales prediction studies (Fantazzini & Toktamysova, 2015; Choi & Varian, 2009a; Carriére-Swallow & Labbé, 2013). The first hypothesis states:

Hypothesis 1: Google Trends volumes are an accurate predictor of new car model sales.

The Google Trends literature stream focuses on the prediction of variables within one country such as the U.S, Germany or Chile (Fantazzini & Toktamysova, 2015; Choi & Varian, 2009a; Carriére-Swallow & Labbé, 2013). A ***cross-country comparison*** of these Google Trends prediction studies provides limited insights because the selected keywords and samples are different. Nevertheless, a comparison of a search engine based prediction potentially unfolds the different properties of search query data and the tool Google Trends across countries. Deloitte (2014) found significant variations in the preferred information sources before the car purchase decision is made. In Germany, Brazil, India, China and Japan word-of-mouth references and the opinion of family and friends are the most important information source. Only the U.S. considers online searches of independent websites as the primary source of information. These differences are assumed to be reflected in the greater volume of internet searches related to a car model in the U.S. and hence in the Google Trends index. The thesis adds to the literature by comparing the accuracy of a Google Trends analysis across countries for the first time. The thesis defines prediction accuracy of the model as the percentage of explained variance in the regression analysis ($\boldsymbol{R^2}$). The same Google Trends keywords and sources for new car sales data are used in both countries to ensure the comparability of the data. It is assumed that the preference for word-of-mouth sources is reflected in a less accurate prediction in Germany compared to the U.S. The second hypothesis states:

Hypothesis 2: The prediction accuracy of Google Trends volumes is higher in the United States than in Germany for new car model sales.

Recent Google Trends analyses published their findings for predictions without the provision of a theoretical explanation (Choi & Varian, 2009a; Carriére-Swallow & Labbé, 2013; Fantazzini & Toktamysova, 2015). Fantazzini & Toktamysova (2015) considered seasonality of internet data for car sales and included further economic variables such as the unemployment rate or the actual state of the economy into the model. Nevertheless, the studies did not consider a certain lead time that a customer needs from the initial information search on the Internet to the final purchase decision. Choi & Varian (2009a) state that predicting the present is associated with predicting sales figures from the last three weeks to three weeks ahead. They point out that "It may also be true that June queries help to predict July sales, but we leave that question for future research" (p. ii). This research also follows the recommendation of Lassen et al. (2014) to consider the existence of their successfully applied time lag for different products than smartphones. A cross-correlation function is used to prove the existence of a lead time between the generation of search engine data and the occurrence in the new car sales data. Magruder (2003) demonstrated the value of a cross-correlation analysis to identify a time lag of three days between the purchase of pharmaceuticals and the physical visit of a doctor. The customer journey from the marketing literature stream serves as a ***theoretical framework*** that allows improving the value of search engine data and explains the outcome of a prediction. Based on the assumption that a tailored time lag exists between information search on the Internet and the final purchase decision, the following hypothesis is stated:

Hypothesis 3: The implementation of the **optimal time lag** into the model increases the prediction accuracy of new car model sales.

Google Trends analyses for car sales treated all car brands equally instead of considering the differences in the buying process for car models, vehicle segments, prices or cultures (Fantazzini & Toktamysova, 2015; Choi & Varian, 2009a; Carriére-Swallow & Labbé, 2013). Fantazzini & Toktamysova (2015) distinguished between large, medium and small sellers. Nevertheless, a seller-based division neglects variations between the car models since a large car manufacturer has a car model portfolio that covers the entire price range from very affordable to highly expensive cars. It is assumed that the price of a car model influences the length of the time lag between problem recognition, and the actual purchase decision as the consumer’s household is affected in the long run (Koklic & Vida, 2009). The purchasing power of the consumer also affects the customer buying behaviour (Waheed et al., 2014). Hence, a linear relationship between the price of the car model and the ***average time lag*** cannot be assumed since a decrease in the consumer buying power can also result in less interest for a low-priced car. The average time lag refers to the sum of the optimal time lags divided by the number of car models under investigation. The following hypothesis is stated:

Hypothesis 4a: The **average time** lag differs between low- and high-priced cars.

Hahn, Choi & Lee (2012) found differences in consumption behaviour between low- and high-involvement goods. However, the involvement of a customer is not always rational and also determined by the customer´s perception of the quality or a certain brand (Kotler & Keller, 2012). The price of the car depends on the underlying car model and ranges from cheap to highly expensive. It is assumed that the vehicle segment influences the average time lag as well. Since the audience for cheap Small-sized cars is supposed to be different from the audience of high priced SUV-Luxury car models, a linear relationship is not presumed. The following hypothesis is stated:

Hypothesis 4b: The **average time** lag differs across vehicle segments.

Cultural differences influence the way how individuals search for information and how decisions are made (Ackermann & Tellis, 2001). Nevertheless, the search engine based prediction literature neglects the consideration of culture so far. The study takes Hofstede´s Dimensions as a further theoretical construct into account to extend the prediction literature stream and to explain the outcome of a Google Trends analysis through a cultural lens. Germans are seen as long-term oriented which is associated with taking care of their resources, a high saving quote and a future-oriented perspective (Hofstede et. al., 2010). Germans also score higher in uncertainty avoidance which is related to the consideration of a high amount of information sources before a buying decision is made (De Mooij, 2010). The short-term orientation of Americans is associated with a fast decision-making process and is assumed to be reflected in a shorter time lag. Germany is considered as a tight country compared to a loose culture in the U.S. (Gelfand et al., 2011). The Tightness-Looseness dimension is supposed to be reflected in preferring secure consumption decisions and using more time for evaluation of alternatives. The thesis assumes that the national culture influences the volume of search queries for particular car models that Germans and Americans submit to search engines. Based on the long-term oriented and risk-avoidant attitude in Germany, the following hypothesis is stated:

Hypothesis 5: The **average time lag** is greater for Germany than for the United States.

Figure 7 illustrates the expected relationship between Google Trends search queries and the volume of new car sales. This relationship is supposed to be moderated by the optimal time lag and the country where the data was generated. Furthermore, the influencing effect of the price/vehicle segmentation and the underlying culture on the length of the average time lag and the optimal time lag are highlighted.

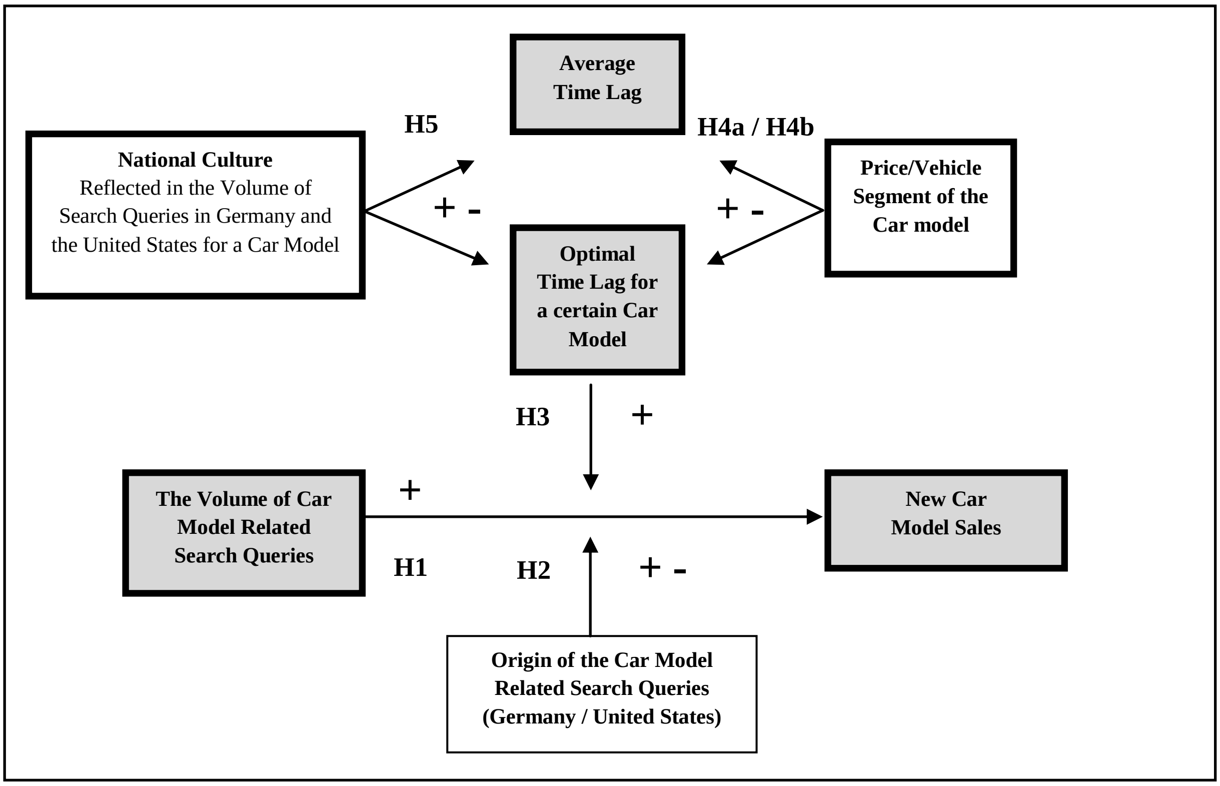

Figure 7: Research Model: Relationship between Google Trends Volumes and New Car Model Sales

4.2 Scope and Data Collection

The free availability of the data and a 2015 search engine market share of 78% in the U.S. and more than 90% in Germany justifies that Google Trends will be used as a source of the search queries in this study (iCrossing, 2015). This research focuses on Germany and the U.S. due to the importance of the automotive industry for both countries by producing more than 10 million cars each year (OICA, 2015). These countries are also characterised by different national cultures that allow investigating variations in consumption habits and search query data. The Chinese market is vital for the automotive industry as well by producing about 20 million cars each year (OICA, 2015). However, the market share of Google Search covers less than 3% in China that limits the comparability of the data (iCrossing, 2015). The thesis focuses on the automotive industry due to the significance of demand planning, the increasing search for new car information online and because decision-makers predominantly use outdated forecasting technologies. The research is limited to fourteen car manufacturers namely Toyota, Volkswagen, Jeep, Kia, Mazda, Audi, Jeep, Porsche, Mini, Mercedes, BMW, Fiat, Ford and Hyundai. The selection was based on the availability of the new car sales data in Germany and the U.S. to ensure comparability across those countries and to increase the reliability of the study.

The keyword selection is one of the major problems to ensure validity and reliability of the thesis. Hence, only car models are selected that are sold under the same name in Germany, and U.S. 24 car models will be tested to get insights of the entire range of the product portfolio. The predetermined models consist of 12 low-, and 12 high-priced car models to control for possible differences in consumer behaviour. A low-priced car relates to a catalogue price up to 27.999€, and a high-priced car model is defined by a catalogue price higher than 28.000€. The German catalogue price for the car models is used for both countries and extracted from the ADAC website[2]. The car models are further grouped into broad vehicle segments close to the classification proposed by the European Commission[3]. Because of the small sample size, the car models are only separated into the Small-size / Mid-size and SUV-Luxury vehicle segments. The Small-size segment includes the car models that are classified as: "*Kleinstwagen"* and "*Kleinwagen".* The Mid-size category contains the car models from the segments: "*Mittelklasse"*, "*Obere Mittelklasse"* and "*Oberklasse".* The SUV-Luxury class stands for the segments: "*SUV (Sport Utility Vehicle)"*, "*Luxusklasse"* and "*Geländewagen"*. The value of a Google Trends analysis will be tested by predicting new car model sales from January 2013 to March 2016. New car sales data from January 2013 to March 2016 are used in addition to Google Trends data for the same period. One car model sample consists of 39 months and exceeds the recommended sample size of 30 data points to ensure the quality of a linear regression model that was proposed by Smailes & McGrane (2000). The time frame is chosen because of the availability of new car sales data in both countries. The maximum time lag to purchase a car is assumed to be 24 months since the

[2] https://www.adac.de/infotestrat/autodatenbank/suchergebnis.aspx
[3] http://ec.europa.eu/competition/sectors/motor_vehicles/legislation/explanatory_brochure_de.pdf

average product life cycle for a new car model is approximately two years as well (Volpato & Stocchetti, 2008). The new car sales data is downloaded from the data centre of Automobilwoche[4] for Germany and the U.S. as a PDF file. The data is available for each month as well as for the predetermined car models separately that ensure the comparability of the dataset. The Automobilwoche Data Centre collects the data on an ongoing basis in the same manner and the same format that enables further Google Trends investigations and increases the reliability of the measure.

This research decreases the sampling impact of Google by extracting the same ***Google Trends data*** on two different days to average both indexes and to increase the reliability of the monthly data. The Google Trends data for each car model is downloaded as a CSV data from the Google Trends website[5]. The exact car model names that are also stated in the new car sales of the Automobilwoche Data Centre are used as the keywords for the analysis. The keyword "Audi Q7" seems to have face validity since it measures users interest for the particular car model. The content validity of Google Search data is increased by enclosing the car model name in quotation marks to exclude searches that are not related to the particular car model. The following Google Trends filters for time, geographical area, as well as categories, are used to increase the validity of the data and to decrease the ambiguity of the keywords: *January 2013-March 2016*; *Germany, United States*; *Automotive & Vehicles*. A new filter possibility that limits the searches to queries directly entered into the *web* engine excludes searches in the categories "*news*", "*images*" or "*videos*". Subsequently, the car model sales data for 24 cars in Germany and the same car models in the U.S. are entered into an Excel sheet. Google Trends data for 39 months for each car model are extracted for Germany, and the U.S. separately and also entered into an Excel sheet to support the subsequent analysis.

The Google Trends data for new car model sales is ***influenced*** by the introduction of a new car model and by consumer´s searching for a second-hand car. Before the decision for the car model name as the keyword was determined, several tests were performed to decrease the influence of second-hand car searchers. As an example, the keyword: "*Audi Q7 -(minus) Second hand*" was assumed to reduce the noise of internet data since it includes searches containing the word "*Audi Q7*" but excludes searches containing the words "*Audi Q7*" and "*Second hand*". The same test was conducted with the keywords "*used*" or "*Gebrauchtwagen"* instead of "*Second hand*". However, Google Trends data is only available if the volume of searches passes a certain (but unreported) privacy threshold (Stephens-Davidowitz & Varian, 2014). This threshold could not be passed with this technique resulting in the following Google error term: "*not enough search volume to show the graphs*". Therefore, the car model name was determined as the keyword in the study without decreasing the influence of second-hand car buyers. The introduction of a new car model also awakens people´s interest. Nevertheless, it is assumed that an increased interest in a newly introduced car model is also reflected in the Google Search volume and the new car model sales data, provided that the car model name remains the same. The car model names chosen as a keyword are not considering the particular car model type. Hence,

[4] http://www.automobilwoche-datencenter.de
[5] https://www.google.com/trends/

searches for the ***Volkswagen Golf 6*** and ***Volkswagen Golf 7*** are both reflected in the Google Trends index for the keyword "***Volkswagen Golf***". The exclusion of queries for the category "Google Videos" further decreases the impact of new car model introductions as it is assumed that videos are also consulted by people that are only interested in the features of a new car model.

4.3 Measurement of the Data

A linear regression is used in this research as it is an appropriate tool to identify relationships between several variables, to test the hypotheses and to implement the time lag (Lassen et al., 2014). A variety of analyses that include internet data used the coefficient of determination R^2 as well as the significance level as measures of the quality of the prediction model (e.g. Choi & Varian, 2012; Lassen et al., 2014; Asur & Hubermann, 2010). The estimation of a linear regression analysis provides these coefficients and can be used to investigate the improvements of implementing a time lag to search engine data. Thus, the method ensures the comparability of the model quality with similar studies. Fantazzini & Toktamysoya (2015) used a far more advanced multivariate model that includes several variables such as seasonality and the GDP of a the economy without considering any time lag. Nevertheless, the advanced regression models are still dependent on the quality of the input variables, and it is assumed that the value of making adjustments to the raw search engine data are better illustrated with less complex models. The software SPSS supports the analysis of the datasets to test the stated hypotheses. The Google Trends data serve as the independent variable in the model, and the new car sales data act as the dependent variable. After accurately preparing the Google data as well as the car model data in Excel, the data is transferred into the software SPSS.

To test ***the first hypothesis***, one linear regression is estimated for the entire new car sales dataset and the whole Google Trends dataset regardless of the car model or the country of origin. The following route through SPSS is used**:** ***Analyze > Regression > Linear*** to estimate the relationship of the datasets. The confidence interval of 95% is taken for testing the relationship between the new car model sales data and the Google Trends data. The remaining 5% ($p=0.05$) are known as the significance level (p-value) of the estimation and justify whether the observed relationship is significant with a 95% confidence level. The thesis also calculates the correlation coefficient "R" as well as "R^2" to assess the direction and the predictive power of the relationship between the investigated variables. The "R^2" value ranges from 0 (zero percent of the Google Trends data can explain the changes in the car sales volume) to 100 (changes in the new car sales data can be fully explained by the Google Trends data) and determines the quality of the model. A positive and significant correlation (positive R, R^2, $p< 0.05$) between both datasets lead to the confirmation of the first hypothesis.

To test the ***second hypothesis*** and to identify differences in the predictability across countries, the datasets of the first model needs to be narrowed down. A regression analysis is estimated for each of the 48 car models separately (2 times 24) based on the origin of the data since the objective is to identify cross-national differences. The estimation is followed by comparing the amount of significant relationships between Germany and the U.S. The second hypothesis is confirmed once the average prediction accuracy and the amount of significant relationships are greater in the U.S. than in Germany.

The test of the ***third hypothesis*** requires the identification of an optimal time lag for all car models within the datasets. The coefficients of the regression analysis without a time lag that were calculated for hypothesis two serve as a benchmark model for the coefficients of the regression analyses that include the time lag. The analysis of the optimal time lag is divided into two parts. Firstly, A cross-correlation measures similarity or diversity of two datasets (Telford, Geldart & Sheriff, 1990) and the following route in SPSS is used: ***Analyze*** > ***Forecast*** **>** ***Cross-Correlation.*** A cross-correlation searches for spikes in one dataset (new car model sales) that are highly correlated to another dataset (Google Trends index) and the method is already used for the identification of a time lag in a similar application field (Magruder, 2003). Through the identification of peak values in the last 24 months of Google Trends data that also occur in the car model sales data, the optimal time lag is identified for each car model. The regression analyses for all car models are ***repeated*** with implementing the identified time lag. As an example, an optimal time lag of one month results in the following changes to the dataset: instead of matching the Google Trends index from January 2013 to the January 2013 car sales data, the Google Trends index from January 2013 will be matched with the sales data from February 2013. As a result, the coefficients (R, R^2, p-value) of the regression models that include the time lag will be compared to the benchmark model that did not consider any time lag. The comparison indicates whether the model fit increases by including a time lag and the third hypothesis can be confirmed or rejected. The total value of implementing a time lag is pointed out by averaging all changes of R^2 across the dataset.

The division into low- and high-priced cars supports the confirmation or rejection of the ***hypothesis 4a***. The average time lag for both price categories is compared. As two time lags are identified for each car model (Germany, U.S.), the average of both time lags is calculated to decrease the effect of outliers and because the origin of the data is not necessary to answer the hypothesis. The division into the vehicle segments Small-size, Mid-size, and SUV-Luxury cars allows testing the ***hypothesis 4b.*** The average time lag of the categories is compared to identify differences in the average time lag associated with the vehicle segment.

Lastly, the identified time lags for the car models are matched to Germany and the U.S. The average time lag for both countries is calculated and compared to test the fifth hypothesis. *The* ***fifth hypothesis*** is confirmed once the average time lag of all car models in Germany is greater than the average time lag for all car models in the U.S.

5. Results

This chapter presents and explains the results of the estimated regression models and the cross-correlation analyses to test the hypotheses. Section 5.1 shows the prediction accuracy in Germany and the U.S. and Section 5.2 demonstrates how the time lag is influenced by the price, the vehicle segment and the national culture.

5.1 Data Analysis and Results: Prediction Accuracy across Countries

The first hypothesis states that Google Trends volumes are an accurate predictor of new car model sales. A linear regression analysis is conducted for the test including all Google Trends indexes as the independent variable as well as all new car sales for Germany and the U.S. Since 24 car models from two countries are considered in this research, and a period of 39 months is investigated, the independent Google Trends variable and the dependent new car sales variable consists of 1872 data points each. ***Table 2*** and ***Table 3*** introduce the outcome of SPSS. ***Table 2*** shows a positive relationship between the Google Trends index and the new car model sales data. The result of R=0.329 indicates a weak but positive relationship between both variables. The coefficient R^2 of 0.108 states that 10.8% of changes in the car model sales data can be explained by changes in the Google Trends index. The adjusted R-Square is neglected in this research because it measures the model quality once more than one independent variable is considered. In comparison to the regression results of Asur & Hubermann (2010) (Adjusted R^2 = 0.94), Choi & Varian (2012) (Adjusted R^2=0.808), and Lassen et al. (2014) (R^2= 0.95), the correlation of this study is weak at the first impression.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	**,329**[a]	**,108**	,108	,61478

Table 2: Linear Regression Results: All Variables

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	,125	,209		,598	,550
	All Variables	1,703	,113	,329	15,059	**,000**

Table 3: Linear Regression Results: Significance Test

Despite the low R^2 of the analysis, ***Table 3*** emphasises the significance at p<0.00 and therefore the first hypothesis is confirmed. The significance proves the existence of a correlation between Google Search queries and new car model sales in Germany and the U.S. The value of the model estimation that includes all variables is very limited for practitioners because no conclusions can be drawn about people´s interest associated with a particular car model or country.

The second hypothesis states that the prediction accuracy of a Google Trends analysis is greater in the U.S. for new car models than in Germany. The scope of the analysis is narrowed down to the car model-level to assess the practical value of the tool. A linear regression model is estimated for all 48 car models to investigate differences in a search engine based prediction across countries. The analysis for the car model ***Audi Q7*** serves as an example for the measurements that are performed for each car model as well as for Germany and the U.S. separately. The linear regression model for the Audi Q7 contains monthly Google Trends and new car sales data for Germany including the period from January 2013 to March 2016 (39months). As illustrated in ***Table 4***, the correlation coefficient *R* of 0.562 shows a medium and positive relationship between the Google Trends index and the Audi Q7 sales data in Germany.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,562[a]	,315	,297	278,370

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-467,598	229,992		-2,033	,049
	Audi Q7	15,094	3,656	,562	4,129	,000

Table 4: Linear Regression Results without a Time Lag (Audi Q7, Germany)

The R^2 measure of 0.315 indicates the quality of the model. Changes in the Google Trends index explain approximately 31.5% of the variance in the new car sales data. In comparison to the first analysis that included all variables (R^2= 0.108), the quality of the model improved by 200% to a value of 0.315. The stated relationship is significant at the level $p<0.00$ that proves the correlation between the new car sales data and the Google Trends index for the car model Audi Q7 in Germany. The same analysis is conducted for all 24 car models in Germany and the U.S. separately, to test the second hypothesis. ***Table 5*** provides insights of the Google Trends analysis for a particular car model as well as for Germany and the U.S. 26 out of 48 cases, or approximately 54% of the models show a significant relationship between both variables. The significant relationships are highlighted in red in the last column. The coefficients of the car model ***Jeep Wrangler*** in the U.S. demonstrate the excellent quality of the model (R^2= 0.626) as well as a strong and positive relationship of 0.791 even without implementing a time lag. This result is already an improvement of approximately 600% (R^2=0.108) in comparison to the first analysis.

Car Model	Linear Regression Analysis without Time Lag			Car Model	Linear Regression Analysis without Time Lag		
Germany				United States			
	R	R^2	P-Value		R	R^2	P-Value
VW Golf	0.048	0.002	0.772	**VW Golf**	0.664	**0.414**	0.000
VW Passat	0.246	0.061	0.131	**VW Passat**	0.344	0.119	0.032
Toyota Yaris	0.272	0.074	0.094	**Toyota Yaris**	0.306	0.094	0.058
Toyota RAV 4	0.466	0.199	0.004	**Toyota RAV 4**	0.643	0.412	0.000
Mercedes C-Class	0.256	0.066	0.116	**Mercedes C-Class**	0.284	0.081	0.080
Mercedes E-Class	0.476	0.227	0.002	**Mercedes E-Class**	0.369	0.136	0.021
Mini Cooper	0.306	0.093	0.059	**Mini**	0.236	0.056	0.147
BMW 3er	0.633	0.401	0.000	**BMW 3er**	0.179	0.032	0.277
BMW 7er	0.095	0.009	0.566	**BMW 7er**	0.131	0.017	0.428
KIA Soul	0.364	0.132	0.023	**KIA Soul**	0.472	0.223	0.002
Audi A5	0.474	0.225	0.002	**Audi A5**	0.711	0.506	0.000
Audi Q7	**0.562**	**0.315**	0.000	**Audi Q7**	0.546	0.298	0.000
Audi A4	0.582	0.338	0.000	**Audi A4**	0.261	0.068	0,108
Jeep Wrangler	0.363	0.132	0.023	**Jeep Wrangler**	**0.791**	**0.626**	0.000
Porsche Cayenne	0.048	0.002	0.771	**Porsche Cayenne**	0.384	0.147	0.016
Porsche Panamera	0.131	0.017	0.426	**Porsche Panamera**	0.073	0.005	0.660
Mazda 2	0.239	0.057	0.143	**Mazda 2**	0.490	0.240	0.020
Mazda 3	0.375	0.141	0.019	**Mazda 3**	0.330	0.109	0.040
Mazda 6	0.401	0.161	0.011	**Mazda 6**	0.354	0.125	0.027
Kia Rio	0.191	0.036	0.245	**Kia Rio**	0.502	0.252	0.001
Kia Sportage	0.459	0.211	0.003	**Kia Sportage**	0.016	0.000	0.925
Hyundai Santa Fe	0.026	0.069	0.105	**Hyundai Santa Fe**	0.205	0.042	0.212
Fiat 500	0.298	0.089	0.066	**Fiat 500**	0.676	0.457	0.000
Ford Focus	0.232	0.054	0.155	**Ford Focus**	0.401	0.161	0.011
Number of Significant Relationships			**11**	**Number of Significant Relationships**			**15**
Average (Significant Results**)**	**0.469**	**0.226**		**Average** (Significant Results**)**	**0.512**	**0.282**	

Table 5: Linear Regression Analysis without a Time Lag for all Car Models

What strikes are the number of significant relationships in Germany and the U.S. 11 out of 24 (46%) car models in Germany show significant results with an average R of 0.469 and an average prediction accuracy of R^2=0.226. In contrast, 15 out of 24 (63%) car models show significant results in the U.S. with a stronger relationship (R= 0.512) and a greater prediction accuracy R^2= 0.282. Hence, 28.2% of changes in the car model sales data in the U.S. can be explained by changes in the Google Trends index and the ***second hypothesis is confirmed*** due to the greater prediction accuracy and the greater number of significant results in the U.S. Nevertheless, only five out of 48 (10.4%) performed regression analyses lead to a coefficient R^2 of above 0.4 and therefore the reflection of people's interest for a particular car model is present but limited so far. The outcome of the regression analysis for each car model offers potential to improvements. There are still 46% of car models in the underlying sample without a significant relationship between the Google Trends data and the new car sales data. However, ***Table 5*** shows that the prediction accuracy of a Google Trends analysis differs across countries and car models.

The third hypothesis stresses the implementation of the ***optimal time*** lag into the regression model to improve the quality and prediction accuracy. The results of the former regression analyses serve as a benchmark to confirm or reject the third hypothesis, dependent on the results of implementing a time lag into the model. The car model Audi Q7 serves as an example of the identification of the optimal time lag for all car models**. *A cross-correlation analysis*** is used to identify the optimal time lag in the first step, followed by the application of the time lag into the regression model in the second step. ***Table 6*** presents the outcome of a cross-correlation analysis or CCF (Cross-Correlation Function) for the Audi Q7 including the upper confidence limit illustrated as a slightly increasing horizontal line to ensure the significance of the identified cross-correlation (time lag). The analysis highlights that a better relationship between Google Trends data and new car sales data for this particular car model in Germany can be estimated with a significant time lag of six months. As a next step, the optimal time lag of six months is applied to the Audi Q7 dataset in the regression model by matching the Google Trends data from January 2013 to the new car sales data for July 2013. The analysis is estimated again with the time lag to evaluate whether significant improvements occur.

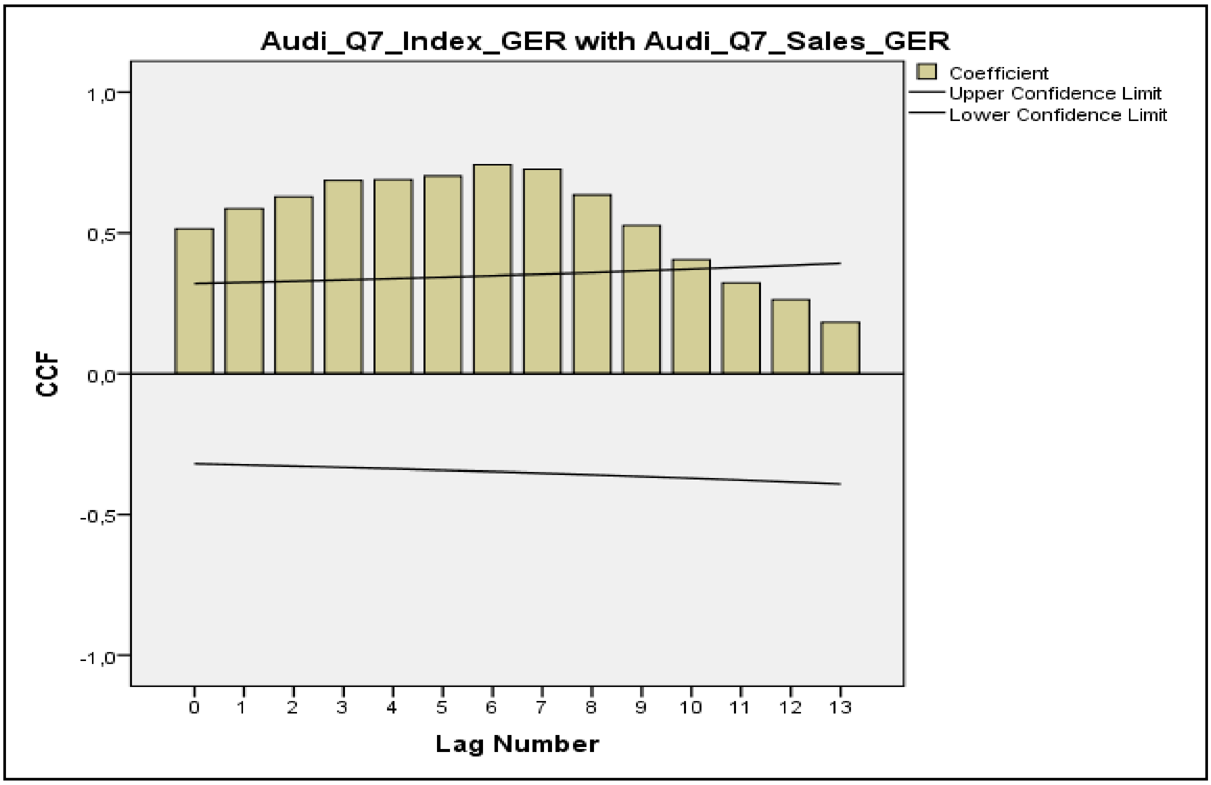

Table 6: Cross- Correlation Analysis: Identification of the optimal Time Lag (Audi Q7, Germany)

Table 7 depicts the application of the optimal time lag for the car model Audi Q7 in Germany and serves as a first indicator to confirm or reject the third hypothesis. The implementation of a six-month lead time results in a strong and significant relationship (R=0.828; p<0.00) between the Google Trends data and the new car sales for Audi Q7 in Germany. The R^2 of 0.685 reveals the excellent quality of the model that even outperforms the former results of the Jeep Wrangler (R^2=0.626). A comparison of the R^2 coefficient (0.685) to the benchmark model (R^2= 0.315) draws attention to the ***value of the time lag*** for this particular car model by improving the quality of the model by 37% as well as the strength of the relationship by 26.6%.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,828[a]	,685	,675	201,29837

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-888,799	171,747		-5,175	,000
	Audi Q7 with Time Lag (6)	22,903	2,791	,828	8,206	,000

Table 7: Application of Six-month Time Lag (Audi Q7, Germany)

The identification and implementation of the optimal time lag are required for all 24 car models as well as for Germany and the U.S. to accept or reject the third hypothesis, ***Table 8*** points out the results of the same analysis performed for the entire sample. The analysis of the 48 car models independent of the underlying country identified 33 significant time lags. The application of the optimal time lag shows model ***improvements up to significant 49.70***% (Mazda 6, U.S.). In approximately 68.75% of the cases, the investigated relationships can be improved by applying the optimal time lag. After the implementation of the optimal time lag, 32 out of the 33 cases (97%), show a significant relationship between both variables at $p<0.05$. The average model improvement of applying the identified lead time is 18.25%. The remaining 13 car models were already significant with the best time lag at month zero and therefore no further improvements by the application of this method are possible. Based on these significant results, the third hypothesis is confirmed. After the implementation of the optimal time lag, 14 out of 48 (29%) regression analyses are characterised by the R^2 coefficient above 0.40 in comparison to only 5 out of 48(10.4%) in the prior analysis. Before the implementation of the optimal time lag, 46% or 22 car model predictions were insignificant. ***Table 8*** also indicates that the number of insignificant findings decreases to 2% since 47 out of 48 cases provide significant results at $p<0.05$. The analysis shows that the implementation of a time lag is of greater value in the U.S. (R^2-Improvement=20.44%) in comparison to also good results in Germany (R^2 Improvement=16.42%). The application of the time lag results in 24 out of 24 significant relationships between Google Trends data and new car model sales data in Germany in comparison to 11 significant relationships without considering the lead time. The average prediction accuracy also increased by approximately five percentage points in Germany to $R^2=0.270$. The sample of the U.S. also greatly benefits from the application of the time lag since 23 out of 24 significant relationships are found, and the average prediction accuracy also increased to $R^2= 0.300$. Therefore, 27% (in Germany) and 30% (in U.S.) of changes in the new car model sales data can be explained by changes in the search query volume of Google on average.

Model	Linear Regression Analysis without Time Lag			Time Lag	Linear Regression Analysis with Time lag			Improvements
Germany	**R**	**R²**	**P-Value**	**Months**	**R**	**R²**	**P-Value**	**R² Improvement**
VW Golf	0.048	0.002	0.772	1	0.369	0.136	0.023	13.40%
VW Passat	0.246	0.061	0.131	2	0.382	0.146	0.020	8.50%
Toyota Yaris	0.272	0.074	0.094	1	0.565	0.320	0.000	24.60%
Toyota RAV 4	0.466	0.199	0.004	1	0.634	0.402	0.000	20.30%
Mercedes C-Class	0.256	0.066	0.116	11	0.384	0.148	0.043	8.20%
Mercedes E-Class	0.476	0.227	0.002	0				
Mini Cooper	0.306	0.093	0.059	2	0.489	0.239	0.002	14.60%
BMW 3er	0.633	0.401	0.000	1	0.724	0.523	0.000	12.20%
BMW 7er	0.095	0.009	0.566	5	0.635	0.391	0.000	38.20%
KIA Soul	0.364	0.132	0.023	0				
Audi A5	0.474	0.225	0.002	0				
Audi Q7	0.562	0.315	0.000	6	0.828	**0.685**	0.000	37.00%
Audi A4	0.582	0.338	0.000	0				
Jeep Wrangler	0.363	0.132	0.023	0				
Porsche Cayenne	0.048	0.002	0.771	2	0.357	0.127	0.030	12.50%
Porsche Panamera	0.131	0.017	0.426	3	0.374	0.140	0.025	12.30%
Mazda 2	0.239	0.057	0.143	2	0.391	0.153	0.017	9.60%
Mazda 3	0.375	0.141	0.019	4	0.407	0.166	0.015	2.50%
Mazda 6	0.401	0.161	0.011	0				
Kia Rio	0.191	0.036	0.245	5	0.589	0.347	0.000	31.10%
Kia Sportage	0.459	0.211	0.003	1	0.667	0.445	0.000	23.40%
Hyundai Santa Fe	0.026	0.069	0.105	7	0.414	0.171	0.019	10.20%
Fiat 500	0.298	0.089	0.066	1	0.383	0.147	0.018	5.80%
Ford Focus	0.232	0.054	0.155	1	0.408	0.166	0.011	11.20%
Average of Significant findings	**0.469**	**0.226**			**0.50**	**0.270**		
Number of Significant Findings (Germany)								**24**
Average Improvement of Implementing the Time Lag into the Model (Germany)								**16.42%**
United States	**R**	**R²**	**P-Value**	**Months**	**R**	**R²**	**P-Value**	**R² Improvement**
VW Golf	0.664	**0.414**	0.000	5	0.719	0.517	0.000	10.30%
VW Passat	0.344	0.119	0.032	1	0.391	0.153	0.017	3.40%
Toyota Yaris	0.306	0.094	0.058	10	0.752	0.565	0.000	47.10%
Toyota RAV 4	0.643	0.412	0.000	0				
Mercedes C-Class	0.284	0.081	0.080	10	0.396	0.157	0.034	7.60%
Mercedes E-Class	0.369	0.136	0.021	0	0.598	0.358	0.002	22.20%
Mini	0.236	0.056	0.147	6	0.278	0.146	0.041	9.00%
BMW 3er	0.179	0.032	0.277	15	0.520	0.270	0.008	23.80%
BMW 7er	0.131	0.017	0.428	2	0.217	0.047	0.196	3.00%
KIA Soul	0.472	0.223	0.002	0				
Audi A5	0.711	0.506	0.000	0				
Audi Q7	0.546	0.298	0.000	0				
Audi A4	0.261	0.068	0.108	3	0.492	0.242	0.003	17.40%
Jeep Wrangler	**0.791**	**0.626**	0.000	**0**				
Porsche Cayenne	0.384	0.147	0.016	0				
Porsche Panamera	0.073	0.005	0.660	12	0.521	0.272	0.005	26.70%
Mazda 2	0.490	0.240	0.020	0				
Mazda 3	0.330	0.109	0.040	6	0.419	0.176	0.015	6.70%
Mazda 6	0.354	0.125	0.027	12	**0.789**	**0.622**	0.000	49.70%
Kia Rio	0.502	0.252	0.001	0				
Kia Sportage	0.016	0.000	0.925	7	0.455	0.207	0.009	20.70%
Hyundai Santa Fe	0.205	0.042	0.212	2	0.476	0.227	0.003	18.50%
Fiat 500	0.676	**0.457**	0.000	0				
Average of Significant findings	**0.512**	**0.282**			**0.50**	**0.299**		
Number of Significant Findings (U.S.)								**23**
Average Improvement of Implementing the Time Lag into the Model (U.S.)								**20.44%**
Average Improvement of Implementing the Time Lag into the Model (Germany, U.S)								**18.25%**
Number of Identified Time Lags (Germany, U.S)								**33**

Table 8: Linear Regression Analysis: Improvements of Time Lag Application for all Car Models

The findings further demonstrate the different properties of a search engine based analysis across countries and show that the unprocessed internet data is of limited value. The usage of internet data requires the identification and application of a time lag to a greater extent in Germany despite the fact that the average improvements are greater in the U.S. Nevertheless, the significance of the relationship is essential in the first place to decrease the likelihood of random and accidental observations. Hence, all relationships in Germany turned significant after the application of the identified lead time. Despite the different effects of taking the time lag into account, the implementation of the time lag is a necessary condition ***in both countries*** as the majority of the findings turned significant and the accuracy highly increased. Therefore, the tool can be used to observe people´s interest for particular car models in Germany and with a greater accuracy in the U.S. for new car model predictions once the data is adjusted.

5.2 Data Analysis and Results: Factors Influencing the Time Lag

Car Model	Car Model Price (€)	Average Time Lag
VW Golf	22.000	3
VW Passat	32.000	1.5
Toyota Yaris	12.000	5.5
Toyota RAV 4	27.000	0.5
Mercedes C-Class	35.000	10.5
Mercedes E-Class	45.000	0
Mini Cooper	20.000	4
BMW 3er	28.000	8
BMW 7er	82.000	3.5
KIA Soul	17.000	0
Audi A5	35.000	0
Audi Q7	61.000	3
Audi A4	31.000	1.5
Jeep Wrangler	37.000	0
Porsche Cayenne	54.000	1
Porsche Panamera	82.000	7.5
Mazda 2	15.000	1
Mazda 3	23.000	5
Mazda 6	26.000	6
Kia Rio	10.000	2.5
Kia Sportage	20.000	4
Hyundai Santa Fe	40.000	4.5
Fiat 500	15.000	0.5
Ford Focus	20.000	3.5
Average Time Lag High Priced Cars (Months)		3.41
Average Time Lag Low Priced Cars (Months)		2.95

Table 9: The Average Time Lag: Low-, and High-Priced Car Models

Hypothesis 4a investigates the effects that a car model price has on the lengths of the already identified time lags. Therefore, the 24 car models are categorised in ***Table 9*** into 12 low-priced (yellow) cars up to 27.999€ and 12 high-priced (green) cars beginning with a catalogue price of 28.000€. The two identified time lags for each car model (Germany, U.S.) are averaged to answer the hypothesis. The origin of the data is not required for this step, and the usage of averages decreases the impact of outliers in the sample. The average time lags for each car model within a price category were added up and divided by the number of cars (12). ***Table 9*** shows that the average time lag for high-priced cars is greater than for low-priced cars. Hence, the average time lag differs between low-, and high-priced cars resulting in the confirmation of the hypothesis 4a. Approximately 3.41 months is the average duration between the problem recognition of individuals to buy an expensive car and the final purchase decision that is reflected in the new car sales. Nevertheless, low-priced cars are also characterised by a lead time of 2.95 months used for information search or the consideration of alternatives. The time lag for high-priced cars is only 0.46 months or less than two weeks longer than for low-priced cars. A longer time lag does not necessarily mean a greater overall search volume in comparison to a shorter time lag. A potential buyer might intensively search for information on the Internet in the first months, followed by talking to friends or experts for several months before the buying decision is made. The largest time lag of the sample is associated to the *Mercedes C-Class* with 10.5 months and might be explained by the fact that the car configuration ranges from a budget car to a highly luxury car. The stated 35.000€ are just the catalogue price of the basic configuration. The price of the Mercedes C-Class can increase up to 85.000€[6] by upgrading the technical components as well as the interior design. Therefore, the configuration and the evaluation of the different car types of the car model, require high involvement of the customer that is reflected the Google Trends index and therefore influencing the time lag for this particular car. The price of 85.000€ is close to the price of the car model Porsche Panamera, which is also characterised by a time lag of 7.5 months. Nevertheless, it is assumed that the purchasing power of individuals that buy a Porsche Panamera is higher than for the audience of the Mercedes C-Class and therefore less involvement and less online searches are required. The particular car model Mercedes C-Class also experienced delivery problems for certain technical components in 2014 that resulted in long delivery periods up to several months[7] that might explain the great time lag as well. Nonetheless, a linear relationship between the price of the car and the average time lag cannot be identified as cheap cars like the Mazda 6 or Toyota Yaris also have a time lag of several months. The Toyota Yaris as the second cheapest car of the entire sample with 12.000€ also has a time lag of 5.5 months. Therefore, it is assumed that the purchasing power of individuals influences the length of the average time lag as well. Individuals who are forced to buy a low-priced car due to their low purchasing power are also likely to investigate a certain amount of time to identify a convincing price-performance ratio that is reflected in the time lag. The findings indicate the importance of considering the specific car models instead of the price solely.

Hypothesis 4 b investigates the relationship between the vehicle segments and the influence on the average time lag. ***Table 10, Table 11 and Table 12*** illustrate the segmentation into Small-size/Mid-Size/SUV-Luxury car models. It strikes that the average time lag for the Small-size vehicle segment is equal to the vehicle segment SUV-Luxury with 2.25 months as presented in ***Table 10 and 11***. This result shows the value of the vehicle segmentation and the consideration of the customer´s purchasing power to get practical insights. It is assumed that the audience of the SUV/Luxury segment has strong purchasing power and does not need a long period to purchase a car. The set of considered car brands and vehicles is already narrowed down to a particular segment and does not require great lead time.

[6] https://www.adac.de/infotestrat/autodatenbank/suchergebnis.aspx

[7] http://blog.mercedes-benz-passion.com/2014/05/keine-auslieferung-von-c-klasse-limousinen-mit-360-grad-kamera-im-jahr-2014/

Small-Size		
Car Model	**Car Model Price (€)**	**Averaged Time Lag**
Toyota Yaris	12.000	5.5
Mini Cooper	20.000	4
KIA Soul	17.000	0
Mazda 2	15.000	1
Kia Rio	10.000	2.5
Fiat 500	15.000	0.5
Average Time Lag Small-Size		**2.25**

Table 10: The Average Time Lag: Small-Size

SUV-Luxury		
Car Model	**Car Model Price (€)**	**Averaged Time Lag**
Toyota RAV 4	27.000	0.5
BMW 7er	82.000	3.5
Audi Q7	61.000	3
Jeep Wrangler	37.000	0
Porsche Cayenne	54.000	1
Kia Sportage	20.000	4
Hyundai Santa Fe	40.000	4.5
Porsche Panamera	82.000	1.5
Average Time Lag SUV-Luxury		**2.25**

Table 11: The Average Time Lag: SUV-Luxury

The audience for Small-sized cars cannot afford a Mid-Size or SUV-Luxury car and focuses on the Small-size segment since the purchase decision of a Small-size car is assumed to be a necessary endeavour. ***Table 12*** points out that the longest time lag was found in the mid-size segment with 2.79 months. A customer of this vehicle segment requires the most time for the final purchase decision that is 0.5 months longer compared to the other segments. The result can be explained by the medium purchasing power of the customers as they might also consider buying a car from the Small-size segment or even from the SUV-Luxury segment. Hence, the evaluation takes more time which is reflected in the average time lag. The results suggest an ***inverted U-shape relationship*** between the vehicle segment and the time lag. Hypothesis 4b is confirmed because significant differences in the average time lag were found across vehicle segments.

Mid-Size		
Car Model	**Car Model Price (€)**	**Averaged Time Lag**
VW Golf	22.000	3
VW Passat	32.000	1.5
Mercedes C-Class	35.000	10.5
Mercedes E-Class	45.000	0
BMW 3er	28.000	8
Audi A5	35.000	0
Audi A4	31.000	1.5
Mazda 3	23.000	2
Mazda 6	26.000	6
Ford Focus	20.000	1
Average Time Lag Mid-Size		**2.79**

Table 12: The Average Time Lag: Mid-Size

The fifth hypothesis draws attention to cross-cultural differences and a longer average time lag in Germany is assumed. The identified time lags for the 24 car models are added up for both countries and averaged as outlined in ***Table 13***. The average time lag in Germany accounts for 2.33 months in comparison to nearly twice of the time in the U.S. with a value of 4.04 months. The finding is contrary to the expected outcome which results in rejecting the fifth hypothesis. Germans require approximately 57% of the time for a new car buying decision that Americans need. A shorter time lag in Germany can also indicate that Germans are searching more intense in a shorter time frame. A greater time lag potentially results from switching between different alternatives. Germany is considered as an uncertainty avoidant country (65) compared to the U.S. (46). It potentially results in trusting and relying on well-known people, dealerships as well as keeping one car brand for a long time. Therefore, fewer car models are considered from the very beginning. Germans also prefer word-of-mouth and talking to family and friends as an information source before a new car is bought, compared to the preference of independent websites in the U.S. Thus, Germans are likely to consider other sources than the Internet at the beginning of the buying process and the Internet is consulted once the car model is already determined. That results in a short time lag of 2.3 months.

Car Model	Car Model Price (€)	Time Lag Germany	Time Lag U.S.
VW Golf	22.000	1	5
VW Passat	32.000	2	1
Toyota Yaris	12.000	1	10
Toyota RAV 4	27.000	1	0
Mercedes C-Class	35.000	11	10
Mercedes E-Class	45.000	0	0
Mini Cooper	20.000	2	6
BMW 3er	28.000	1	15
BMW 7er	82.000	5	2
KIA Soul	17.000	0	0
Audi A5	35.000	0	0
Audi Q7	61.000	6	0
Audi A4	31.000	0	3
Jeep Wrangler	37.000	0	0
Porsche Cayenne	54.000	2	0
Porsche Panamera	82.000	3	12
Mazda 2	15.000	2	0
Mazda 3	23.000	4	6
Mazda 6	26.000	0	12
Kia Rio	10.000	5	0
Kia Sportage	20.000	1	7
Hyundai Santa Fe	40.000	7	2
Fiat 500	15.000	1	0
Ford Focus	20.000	1	6
Average Time Lag Germany (Months)		**2.33**	
Average Time Lag United States (Months)			**4.04**

Table 13: The Average Time Lag: Germany and the United States

Despite rejecting the fifth hypothesis, the national culture and relying on well-known and trusted sources are still reflected in the results of the analysis and also in line with the high tightness-score in Germany. It is assumed that the individualistic culture in the U.S. is reflected in searching for new car information before other sources are used which is reflected in a longer lead time. The time lag for certain car models also ***introduces noise*** in the data. For the ***Toyota Yaris*** (12.000€) a time lag of 10 months is identified in the U.S. compared to one month in Germany. It can be assumed that this car is bought by Americans who have to take care of their resources and therefore investigate more time in the consideration of alternatives. The time lag of zero for particular high-priced cars also attracts attention, including the Mercedes E-Class and the Audi A5. Both car models are highly used as business cars. Also, the car models VW Golf, BMW3 and Audi A4 are amongst the top five business cars in Germany[8]. However, these car models are not considered as business cars in the U.S. This serves as an explanation for the huge differences in the time lags for these car models between both countries. Company cars are often managed with long-term contracts that are not reflected in the Google Search volume and therefore cannot be explained by the national culture. What particularly strikes is the significant difference in the time lags for the ***German car manufacturers*** Volkswagen, Audi, BMW and Porsche that was also examined in the literature. ***Table 14*** shows the extracted time lags for German car manufacturers from the entire sample that result in a short average time lag in Germany (2.8 months) compared to 4.4 months for Americans. The results potentially prove that the national culture still serves as an additional indicator for differences in the buying decision. Germans have a cultural configuration of a high degree of uncertainty avoidance (65) ***and*** masculinity (62) that relates to the preference of cars that are well-designed, technologically advanced and safe. The combination of these two cultural dimensions and the vehicle attributes that are also associated with German car manufacturers potentially explain the short time lag in Germany compared to Americans.

German Car Manufacturers			
		Time Lag	
Car Model	Car Model Price (€)	Germany	U.S.
VW Golf	22.000	1	5
VW Passat	32.000	2	1
Mercedes C-Class	35.000	11	10
Mercedes E-Class	45.000	0	0
BMW 3er	28.000	1	15
BMW 7er	82.000	5	2
Audi A5	35.000	0	0
Audi A4	31.000	0	3
Audi Q7	61.000	6	0
Porsche Cayenne	54.000	2	0
Porsche Panamera	82.000	3	12
Average Time Lag		2.8	4.4

Table 14: The Average Time Lag: German Car Manufacturers

The combination of a low degree of uncertainty avoidance (U.S, 46) but a high degree of masculinity (U.S, 62) relates to the preference for big and powerful cars and especially towards the vehicle segment SUV. ***Table 15*** shows the extracted data for the vehicle segment SUV and highlights the short time lag of only 1.125 months in the U.S. which is in line with the configuration of these two cultural dimensions. The findings suggest that particular cultural dimensions are more reflected in search engine data than others since the long-term orientation or the preference for secure decisions in

[8] http://www.spiegel.de/fotostrecke/top-10-der-beliebtesten-dienstwagen-2012-fotostrecke-99264-2.html

Germany potentially influences whether the Internet is used for information search at all. The results point out that the time lag is influenced by a variety of aspects and that the national culture itself only serves as a complementary explanation for particular findings.

SUV			
Car Model	Car Model Price (€)	Time Lag	
		Germany	U.S.
Toyota RAV 4	27.000	1	0
Audi Q7	61.000	6	0
Jeep Wrangler	37.000	0	0
Porsche Cayenne	54.000	2	0
Kia Sportage	20.000	1	7
Hyundai Santa Fe	40.000	7	2
Average Time Lag SUV		**2.125**	**1.125**

Table 15: The Average Time Lag: SUV

6. Discussion and Future Research Potential

Chapter 6 draws attention to the key results of the study and refers to the hypotheses as well as the central research question. The discussion embeds the underlying research into a broader picture and emphasises the academic contributions. A comparison to related Google Trends analyses for car sales provides insights into the achievements of the study. The chapter concludes with future research potentials and limitation of the thesis.

6.1 Key Findings

The Literature Review

The literature review and the analysis of the relationship between Google Trends data and new car sales deliver valuable insights to answer the research question of the thesis: ***How does a Search Engine based Prediction differ across Countries for New Car Model Sales*?** The review of the literature pointed out that car manufacturers are faced with difficulties in demand planning across countries but still rely on outdated forecasting technologies (Dharmani et al., 2015). However, the value of internet data to predict and forecast sales figures is confirmed by several researchers (Ettredge et al., 2005; Fantazzini & Toktamysova, 2015). The investigation of different buying decision models from the marketing literature found significant variations in people´s consumption behaviour (Hahn, Choi & Lee, 2012; Kotler & Keller, 2012). The differences are based on the type of product including the time spent for information search but also the amount of invested resources (Ackerman & Tellis, 2001). The national culture exerts influence on consumer habits as well. Based on Hofstede´s Dimensions, cultural differences were found between Germany and the U.S. (Hofstede et al., 2010). Germany is considered as a state that tries to avoid uncertainty in addition to preferring secure decisions, rules and regulation. The U.S. is found as a short-term oriented and individualistic culture with low scores in uncertainty avoidance (Hofstede et al., 2010). The potential of the tool Google Trends for predictions is outlined with significant results in a variety of application fields that point to the explanatory power of search engine queries (Stephens-Davidowitz & Varian, 2014). Google Trends data possess several limitations, but the simplicity and practicability compared to a traditional survey increase the value for researchers and practitioners.

Data Analyses

Several linear regression models and cross-correlation analyses were estimated to answer the five hypotheses of this research. ***The first hypothesis*** is supported since a significant relationship between new car model sales data, and the Google Trends index was found. Despite the fact that the relationship (R= 0.329) and the predictive performance (R^2= 0.108) are weak, the results are in line with the findings of similar studies. 10.8% of changes in the new car model sales data can be explained by changes in the Google Search query index. Nevertheless, the data was not matched to a particular country or car model and only served as a starting point for the analysis. The results of the analysis without a time lag lead to the confirmation of ***the second hypothesis*** due to significant differences in the predictive performance of a Google Trends analysis between the U.S. and Germany. The findings reveal that 46% of the analyses show significant results for Germany in comparison to 63% of significant relationships in the U.S. The average predictive accuracy of the significant results is also higher in the U.S. (R^2=0.282) than in Germany (R^2=0.226). Thus, 28.2% of changes in the sales data can be explained by the variance in the search query data in the U.S. on average. Regardless of the origin of the data, 26 out of 48 car models (54%) show a significant relationship between both variables. The investigation of the ***car model-level*** revealed that 62.6% of the variance in the new car model sales data of the Jeep Wrangler in the U.S. can be explained by changes in the volume of the Google Trends index. Nevertheless, 46% of all car model analyses remain insignificant without implementing a time lag. The cross-correlation analyses identified for 33 out of 48 car models significant time lags and the prediction accuracy in Germany and the U.S. also increased. The average improvements of applying the time lag were 18.25% in total, 20.44% in the U.S. and 16.42% in Germany that lead to the confirmation of the ***third hypothesis.*** The implementation of the time lag results in 98% of significant relationships between Google Trends and new car sales data in comparison to only 54% of significant correlations before the time lag was introduced. What strikes is the finding that all relationships in Germany turned significant compared to 96% in the U.S. The implementation of the time lag also improved the value of the analysis for particular car models since the prediction accuracy of the Audi Q7 in Germany ended up at R^2=68.5%.

Hypothesis 4a is supported as well as this research found disparities in the average time lag associated with the price of the car model. The average lead time for low-priced cars was found at 2.96 months in comparison to 3.41 months for a high-priced car. The consideration of the vehicle segments Small-size, Mid-size and SUV-Luxury leads to the confirmation of ***Hypothesis 4b.*** The average time lag differs across these vehicle segments with the longest lead time until the purchase is made for the Mid-sized car models (2.79 months). The time lags for the category SUV-Luxury and Small-sized cars are of equal size with 2.25 months. The purchasing power of the customer serves as an explanation for the finding as an inverted U-shape relationship was identified for the vehicle segmentation. The ***fifth hypothesis*** investigated the influence of the national culture on the average time lag. The average time lag for car models in the U.S. (4.04 months) is larger than the average time lag in Germany (2.33 months) that leads to the rejection of the hypothesis. This finding is contrary to the initial expectations that were based on researchers previous findings and the consideration of Germans as an uncertainty avoidant and long-term oriented culture. Nevertheless, the preference for German car manufacturers or the vehicle segment SUV, dependent on the combination of the dimensions of uncertainty avoidance and masculinity was verified in the sample. Americans prefer big and powerful cars reflected in a short time lag for the vehicle segment SUV (1.125 months), and Germans prefer safe and well-tested cars reflected in the short time lag for German car manufacturers. The investigation of the relationship between the national culture and the length of the buying process were influenced by car models that have different purposes in both countries since the most common business cars in Germany are not perceived as such in the U.S. Hence, the cultural dimensions are not equally reflected in the search query volumes.

Summary

The findings support the decision to focus on the car model name as search engine keywords since a ***significant*** and positive relationship between the Google Trends index and the new car model sales data were found. The thesis proved the potential of the tool Google Trends for new car sales predictions once the search engine data is ***adjusted*** and the scope of the analysis is narrowed down to the country-, or car model-level. However, Google Trends is a weak predictor of new car sales, prone to errors and the value for decision-makers and researchers is very limited ***without any adjustments*** of the dataset. The consideration of a theoretical framework enabled the justification of a time lag in the data. The existence of a time lag in search engine data was confirmed in Germany and the U.S. The application of a time lag into the model radically improved the overall prediction accuracy of the tool Google Trends and decreased the dependence on chance. The implementation of a time lag is a ***necessary condition*** to get constructive insights in Germany and the U.S. but the average ***improvements are greater in the U.S.*** The adjustments of the raw search engine data and the precise keyword selection allow for the usage of Google Trends as a complementary and tailored tool to observe people´s interests for particular car models with a ***greater accuracy in the U.S.*** than in Germany. Nevertheless, the significant findings in Germany also enable the application of a search engine based prediction in Germany once the researcher is willing to sacrifice little accuracy. The link to the customer journey served as an explanation for differences in consumption behaviour which increases the understanding of the entire market. The ***optimal*** and ***average time*** lag for the car models differ according to the price, the vehicle segment and across countries. The national culture sheds light into the findings of a Google Trends analysis to some extent and provides additional insights that go beyond the obvious. Nevertheless, many factors are influencing people´s interest for a particular car model and the sole consideration of the national culture is of limited value for decision-makers.

6.2 Discussion

Predictions and Forecasting with Internet Data

Shmueli & Koppius (2010) draw attention to the value of ***predictive analytics*** as a key activity in science that consists of data predictions, but also includes the evaluation of the predictive performance. They state that there are the following six ways to contribute to the literature of predictive analytics: “discovering new relationships potentially leading to new theory (1), contributing to measure development (2) improving existing theoretical models (3), comparing existing theories (4), establishing the relevance of existing models (5), and assessing the predictability of empirical phenomenon (6)” (p. 38).

The thesis adds to the literature of predictive analytics by ***improving the prediction accuracy of a model*** that includes internet data which highlights the significance of this work for the research stream. Shmueli (2010) states that explanatory models rely on theory and predictions rely on data. This research emphasises the ***importance of a theoretical construct for predictions*** to identify new observations or patterns that were not obvious in the original model. The link to the marketing and cross-cultural literature enabled to explain the outcome of a statistical model, to reduce the risk of random results, and to capture complex patterns. Hence, the distinction of Shmueli (2010) for explanatory modeling and predictive modeling is too sharp since predictions can also benefit from theory as illustrated in the thesis. The thesis (search engine data) and the work of Lassen et al. (2014) (Twitter data) point to the ***existence of a time lag*** between the data generation on the Internet, and the actual occurrence of buying which is reflected in the sales data. Before the search engine data was adjusted, the model of this thesis was simply testing a causal hypothesis in line with the definition of an *explanatory* model. The thesis stresses the ***necessity of the time lag*** for predictions and also for forecasting once internet data is used because it improves the explanatory power and the value of internet searches which is crucial for researchers and practitioners. Reijden & Koppius (2010) improved the predictive accuracy of their model up to 28% by including the raw internet data. This study increased the predictive accuracy of the model up to 49.7% not by simply including internet data, but by identifying new patterns within the internet data and by improving the value of search engine data to predict economic variables.

Rieg et al. (2010) found no improvements in the ***forecasting*** accuracy in the last 15 years by considering changes in the forecasting error over this period. They state that forecasts that are based on extrapolating time-series trends are faced with the increasing sales volatility, and the forecasting error will even increase in the future. The cross-correlation analysis accounts for up-to-date patterns within the data that go beyond seasonality and allows predicting future values instead of predicting the present. Forecasts are considered as more complex than predictions by taking more variables and a longer forecast horizon into account. The findings are also beneficial for the extrapolation of trends in the forecasting context to decrease the impact of cross-national demand volatility in the automotive industry. The thesis provides forecasting scholars with an advanced and tailored web data variable that is derived from the ubiquitous amount of search queries. Hence, the modification of raw search engine data offers potential to decrease the out-of-sample forecasting error as well.

Comparison with Google Trends Literature

Choi & Varian (2009a; 2012) used the tool Google Trends to predict motor vehicle parts sales and automotive sales with a less appropriate ***keyword selection procedure***. On the one hand, the car brands as keywords to predict car sales are useful to emphasise the value of the tool Google Trends for predictions. On the other hand, the keywords have limited value for decision-makers in the automotive industry. The thesis determined the exact car model name as a keyword to support the significant findings of Choi & Varian but also to add value for practitioners by illustrating people´s interest for a particular car model. This study draws attention to the value of a Google Trends analysis and motivates researchers to determine more focused and practically useful keywords. Choi & Varian (2009a) used a survey based approach to collect the sales data of the motor vehicle parts from car dealers. The repeatability suffers from this technique since surveys potentially result in non-response, and different dealers might sell different car models as well. The thesis extracted the car sales data from a huge and well-known database that collects and prepares the data in the same manner for years and therefore can be used for further investigations as well. The structured and advanced ***keyword selection and data collection*** of the thesis can be seen as the first difference to the literature. Choi & Varian (2009a; 2012) also used a regression analysis to test the relationship between the Google Trends index and the car sales data. The quality of the model was tested by taking a look at the R^2 coefficient and the Mean Absolute Error (MAE) between a benchmark model that did not include Google data and the model including this type of data. The underlying thesis estimated ***linear regression*** models and illustrated improvements as well as the overall quality of the model by considering the coefficient of determination R^2. One major difference between the thesis and the work of Choi & Varian (2009a; 2012) is found in the ***implementation of a time lag***. Choi & Varian (2009a; 2012) claimed to predict the present instead of predicting the future. They examined the volume of search queries in June to predict the car sales in June without considering differences in the lengths of information search. Their approach might work in cases where the time lag of the investigated product is zero and no adjustments of search engine data are necessary. The study at hand stresses the ***importance to check*** for the existence of a time lag once internet data is used to ***predict future values*** and to improve the reliability and validity of the model. According to the definition of Shmueli (2010), predicting the present is ***not*** considered as a prediction since no new or future observations are identified. The prediction accuracy for particular car models (R^2= 0.685) in the thesis are close to the performance of Choi & Varians (2012) study (R^2= 0.808) but the results of the underlying research can be traced down to a car model and country that is important in the context of sales forecasting.

Fantazzini & Toktamysova (2015) investigated the relationship between new car registrations in Germany, the Google Trends index but also several economic variables such as the consumer price index or the unemployment rate. The thesis consciously limits the model to the Google Trends index as the independent variable to evaluate the prediction performance across countries. Nevertheless, the implementation of further economic variables needs to be considered in more advanced models that are estimated in the future. Fantazzini & Toktamysova (2015) categorised the investigated car brands into small, medium and large sellers based on the average sales of the car make without finding any differences in prediction performance. This thesis found significant differences in the prediction performance of a Google Trends analysis across car models and emphasises the classification of the car models instead of the car manufacturer. The statistical model in the thesis is less advanced in comparison to the multivariate models of Fantazzini & Toktamysova (2015). However, this research stresses the application of adjusted internet data which is also beneficial for more sophisticated models. The purpose of this work and the study of Fantazzini & Toktamysova (2015) can be seen as a further difference. Fantazzini & Toktamysova (2015) evaluated the strengths and weaknesses of a huge set of models that include Google Trends data as well as several economic variables to forecast up to 24 months ahead. This study pursued the objective to identify differences in a search engine based prediction across countries and to improve the prediction accuracy of search queries with an optimal time lag.

The compared studies provide vital contributions to the literature stream. Choi & Varian (2009a; 2012) serve as a motivation for other researchers by drawing attention to the possibilities of a Google Trends analysis. Fantazzini & Toktamysova (2015) followed the first call of Choi & Varian (2009a) to apply Google Trends data in more advanced and multivariate models for long-term forecasts. The underlying research followed the second note of Choi & Varian (2009a) as they assumed that queries from the previous month might also support predictions in the following month. This study proposed a way to improve the value of raw internet data on the product-level and performed the first cross-country comparison of a search engine based prediction with results in favour for the U.S**.** The Google Search queries in the U.S. are more accurately reflecting people´s interests for the determined car models on average. Nevertheless, the demand planning for particular car models can greatly benefit in both countries as 68.5% (62.6%) of changes in the new car sales data for the Audi Q7 in Germany (Jeep Wrangler in U.S.) can be explained by changes in the Google Trends index. Choi & Varian (2009) and Fantazzini & Toktamysova (2015) solely considered the Google Trends literature stream in their studies. This research embeds the Google Trends analysis into a broader picture and sheds light on the mechanisms behind the prediction outcome by creating a link to Hofstede´s Dimensions from the cultural literature and the buying decision process from the marketing literature. The thesis increases researcher’s awareness of the ***different properties*** of search engine based predictions across countries and shows the limited value of unprocessed internet data. Fantazzini & Toktamysova (2015) and Choi & Varian (2009a; 2012) neglected the limitations of web data and the threats to reliability and validity of the analysis. This work compared the value of a Google Trends analysis to a traditional survey and demonstrated how to decrease the noise of the data. The study also stresses the absence of a ***“one-fits-all***” approach for search engine based predictions since the model has to be adapted to the specific application fields, countries and products that are characterised by unique properties.

6.3 Limitations and Future Research

The comparison of the Google Trends analysis in this thesis is only limited to Germany and the U.S. despite the importance of China for the automotive industry. A cross-country comparison of a search engine based prediction for other products than cars potentially support the findings of this research. The study is narrowed down to 24 car models that are selected based on the availability of the new car sales data to ensure reliability as well as comparability of the research. Therefore, the car model sample can be increased in the future to enhance the value for specific car manufacturers. The comparison of more than two countries is left as endeavours for future researchers. Particularly in the context of cross-cultural differences, the investigation of Asian countries potentially shed further light on the reasons behind the existing differences in search engine based predictions. The thesis indicates the benefits of combining adjacent research streams to the Google Trends literature which encourages scholars to create further linkages to Google Trends in the future. The vehicle segmentation of this study was limited to three categories and consists of a small sample size. Future researchers potentially investigate the vehicle segments in more detail with additional car models to examine new insights. A further point of improvement can be seen in using not only Google Trends data as the independent variable. Automotive sales are influenced by a variety of factors such as the economic state, political decisions of the country as well as seasonality which need to be considered in the future. The Google Trends analysis is based on internet data and therefore does not provide a tool with 100% accuracy. Hence, Google Trends data for car models are influenced by individuals searching for a car without any intention to buy. The interest for a certain car model cannot be narrowed down to a particular target group to develop tailored marketing activities from a decision-makers viewpoint. The ***dependency on the Google Trends sampling procedure*** and the fact that even minor changes in the keywords, the region or the time frame result in a completely different Google Trends index is one big limitation of this research. The absolute volume of Google Search queries is unreported which affects the generalisability of the study because it remains unclear whether 100 or 10.000 users are interested in a topic. Thus, the thesis is based on several assumptions. This research was also not able to exclude the search queries of users that are interested in second-hand cars which introduces noise in the data and affects the quality of the model. The thesis identified the value of a time lag for new cars and therefore encourages future researchers to apply the identification and implementation of a time lag into their prediction models for different products such as houses or electronic goods. Think with Google (2015) states that there is an increase in people watching car reviews on YouTube before buying a car, and 69% were influenced by the videos in their buying decision. Thus, analysing YouTube Trends instead of Google Trends to further support the car sales forecasting is a future research direction that offers additional potential.

The development of ***guidelines*** how to use the tool Google Trends is still in their infancy. ***Seven*** practical considerations potentially improve the value of a Google Trends analysis. ***Firstly***, the more precise and practical-oriented the keywords and regions are determined, the better the performance of the analysis and the more beneficial the insights. The reliability of the analysis can be improved by selecting stable keywords that enable the repetition of the request for a certain period. ***Secondly***, the Google Trends filter selections serve as a possibility to narrow the scope of the study and to increase the validity as it ensures to investigate the intended issues. ***Thirdly,*** a Google Trends analysis is most appropriate to investigate short-term trends due to the changing composition of internet users and the increasing volume of search queries. ***Fourthly***, the raw search engine data requires a test for a possible time lag to reduce the dependency on chance and the risk to discover random observations in the prediction of economic variables. ***Fifthly***, the time lag needs to be applied to the model, and a repetition of the analysis allows testing for improvements in the prediction accuracy. ***Sixthly***, a link to an appropriate theoretical framework supports the explanation of the results and improves the quality of the entire study. ***Lastly***, one has to be aware of the search engine data limitations and the factors influencing the validity and reliability of the research. These considerations enhance the transparency, the comparability and the generalisability of studies that use search engine based data in their analysis.

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