Jg. 2 · Heft 1 · November 2021

Research Journal for Applied Management

Inhalt

Herausgeber: Prof. Dr. Ingo Böckenholt,
Prof. Dr. Kai Rommel

Research Journal for Applied Management
Jg. 2, Heft 1

ISM International School of Management
Prof. Dr. Ingo Böckenholt; Prof. Dr. Kai Rommel (Hg.)

Um aus dieser Publikation zu zitieren, verwenden Sie bitte diesen DOI Link:
https://doi.org/10.22602/IQ.9783745870688

Bibliografische Information der Deutschen Nationalbibliothek:
Die Deutsche Nationalbibliothek verzeichnet diese Publikation in der Deutschen Nationalbibliografie; detaillierte bibliografische Daten sind im Internet über dnb.dnb.de abrufbar.

publIQation
ACADEMIC PUBLISHING

PubliQation – Wissenschaft veröffentlichen

Ein Imprint der Books on Demand GmbH, In de Tarpen 42, 22848 Norderstedt

Chefredaktion: Till Barchfeld
Gestaltung: Sabine Pillath-Günthner
Vorsitz Wissenschaftlicher Beirat: Prof. Dr. Kai Rommel

Herstellung und Verlag: BoD – Books on Demand GmbH
In de Tarpen 42, 22848 Norderstedt

ISBN Print 978-3-7458-7060-2

ISBN ePDF 978-3-7458-7068-8

Inhalt

Editorial

Das **Research Journal for Applied Management** (RJAM) präsentiert den Leserinnen und Lesern in der Ausgabe 1/2021 Ergebnisse aus der praxisorientierten Forschung zu verschiedenen Managementthemen. Die Beiträge dieser Ausgabe stellen Ergebnisse aus der Risikoanalyse, der Finanzpolitik, des Influencer-Marketings und des Datenzugriffsrisikos vor.

Der Beitrag von **Samunderu** und **Küpper** stellt in zwei Teilen die Ergebnisse einer „Commodity Risk Analysis“ vor. Im ersten Teil “Deconstructing commodity risk analysis” werden auf Grundlage eines systemdynamischen Modells die Auswirkungen des Rohstoffrisikos auf die Kapazitätsprognose von Fluggesellschaften untersucht. Im Fokus steht die Änderung des Spot Price für Kerosin auf die durchschnittlichen Flugpreise auf dem US Amerikanischen Inlandsmarktes. Der zweite Teil „Testing the impact of commodity risk on airline ca-pacity forecasting” übernimmt eine empirische Methode zur Prüfung des Rohstoffrisikos bei der Kapazitätsprognose von Fluggesellschaften

Friesendorf und **Durai** untersuchen in Ihrem Beitrag „Testing the Generalized Fisher Hypothesis for Post-Unification Germany” die Gültigkeit der verallgemeinerten Fisher-Hypothese für das wiedervereinigte Deutschland zwischen Januar 1991 und März 2020 mit Hilfe der kontinuierlichen Wavelet-Analyse.

Der Beitrag von **Edler** und **Perret** „Who Influences the Influencer – First Approaches towards a Quantitative Influencer Marketing“ geht auf Basis von Daten des Sozialen Netzwerks Instagram der Frage nach, wie Beziehungen zwischen Influencern mit einem Schwerpunkt in der Damenbekleidung und deren Relevanz im Netzwerk, mathematisch modelliert messbar gemacht werden kann. Ebenso wird der Frage nachgegangen, in welchem Ausmaß internationale Verflechtungen zwischen den Influencern bestehen.

Seidler, Bingemer und **Brandt** befassen sich in Ihrem Beitrag mit dem Titel „Wahrgenommenes Datenzugriffsrisiko im Kontext von Big Data“ mit den negativen Effekten der Sammlung und Verwendung von Kundendatensammlung. Untersucht wird, wie das wahrgenommene Datenzugriffsrisiko sowie die Ehrlichkeit eines Unternehmens sich auf das Konsumentenvertrauen und die Kundenbindung auswirken.

Ein besonderer Dank geht an die Gutachterinnen und Gutachter dieser Ausgabe und an das Editorial Board für die inhaltliche Bewertung der eingereichten Beiträge. Auch beim Team der ISM-Bibliothek und den Mitarbeiterinnen des Forschungsdekanats möchten wir uns für die erfolgreiche Umsetzung des Research Journal for Applied Management bedanken. Beim Lesen dieser Ausgabe wünschen wir allen Leserinnen und Lesern viel Spaß und freuen uns über die Einreichung von Beiträgen für die nächste Ausgabe des Research Journal for Applied Management. Der Call for Papers befindet sich am

Ende des Journals. Weitere Informationen zum RJAM finden Sie unter folgendem Link: http://ism.de/research/research-activities.

Dortmund im November 2021

Samunderu, Eyden; Küpper, Yvonne

Deconstructing commodity risk analysis: A theoretical perspective from the airline industry – Part 1

Received 19.08.2020 · Received in revision 17.11.2020 · Accepted 08.09.2021

Abstract

This paper implies the testing of the impact of commodity risk on airline capacity forecasting, which is based on a system dynamics framework. The urgency for this investigation has been derived from the airline industry's most severe challenge – the profit cyclicality. There, capacity forecasting is considered to be one of its key drivers. It is merged into the starting point of airline capacity planning – forecasting. An extensive literature review implies the essential elements of the paper – risk management, forecasting, and the critical characteristics of the airline industry.

Keywords: Capacity forecasting, Risk assessment, risk mitigation, systems dynamics, jet fuel spot price and profit cyclicality

1 Introduction

The airline industry presents a paradox (Doganis 2006). From a profit perspective, the industry has demonstrated high levels of cyclicality and very prone to exogenous shocks such as oil spikes, terrorist activities and geopolitical tensions. Cronrath (2018) incorporates drivers of the profit cyclicality from all levels of the aviation business and identifies airline's underutilized capacity as one of them. At the same time, the notion of risk management becomes relevant as unnoted risks lead to further losses and hence, would impede the disruption of the airline industry's profit cyclicality (cf. Waite 2012). As forecasting is indispensable for successful corporate planning (cf. Makridakis et al. 1998: 2), it implies the beginning of capacity planning. Furthermore, early identification of risk factors may be essential for providing suitable mitigation measures, the assessment and measure of possible risk factors seem necessary to be integrated within the approach of forecasting. Over time the industry has also witnessed a surge in competition along many dimensions such as air fares, passenger load factors and route networks (Samunderu 2016)

The airline industry is shaped by an enormous cyclicality in economic results, moving from record high profits to massive losses since the beginning of its existence. One specific reason for this phenomenon has not been identified yet but a number of drivers, which have been analyzed through the doctorate of Cronrath (2018). She incorporates drivers of the profit cyclicality from all levels of the aviation business and identifies airline's underutilized capacity as one of them. At the same time, the notion of risk management becomes relevant as unnoted risks lead to further losses and hence, would impede the disruption of the airline industry's profit cyclicality (cf. Waite 2012). As forecasting is indispensable for successful corporate planning (cf. Makridakis et al. 1998: 2), it implies the beginning of capacity planning. Furthermore, early identification of risk factors may be essential for providing suitable mitigation measures, the assessment and measure of possible risk factors seem necessary to be integrated within the approach of forecasting. Therefore, the motivation for this thesis involves the first step of relating two challenges within the airline industry by investigating the impact of risk management on capacity forecasting.

2 Literature Review

In the context of business administration, the word risk is understood as a parameter, which could result in a financial loss (cf. Waite 2012). Therefore, corporations tend to avoid threats in order to ensure their business models remain sustainable. However, taking risks is often necessary to strive for progress and development, which is even more essential regarding sustainability (cf. Ebersoll/Stork 2016: 31-32). Jorion specifies the issue even further by stating that risks can never be entirely avoided. More generally, "the goal is not to minimize risks; it is to take smart risks" (Jorion 2011: 3).

This results in the necessity of appropriate risk management, which proves itself as challenging due to risks being variable and having different characteristics. Consequently, risk management has to be considered as a process, which identifies, assesses, measures and manages risks to create economic value (cf. Rausand 2013: 3). Regarding the measurability of risks, it is deduced that these can be assessed quantitatively via statistical approaches, which leads to the conclusion of risks having probabilities. The probability distribution of profits and losses considers the quantitative part of the risk assessment process, which accounts for a qualitative part as well. However, this will be elucidated further in the sub section regarding risk assessment.

According to the previous paragraph, it is already notable that risk management is a complicated issue, which needs thorough deconstruction. Above it has been mentioned that it is essential to identify risks. As its dynamic environment characterizes today's business world, new sources of risks emerge all the time. Therefore, a continuous identification procedure is essential to provide successful risk management.

Sources of risks can be identified in many ways. An approach considering risk categorization can improve the process of risk structuring. For instance, Jorion (2011) starts off categorizing risks by their level of perceptibility and distinguishes them by their likeliness to be known and to be considered within the risk assessment process. He labels the first category as the "known," which can be assessed as being accurately definable and measurable risk factors, even though, losses can still occur due to the probability distribution of profit and loss. Further on, the classification named "known unknowns" considers weaknesses within the risk models, inaccurate measurement of volatilities and correlations as well as an incorrect mapping process. The third category describes the "unknown unknowns," which represent the occurrence of a scenario entirely out of scope, which are among others restrictions and governmental regulations. (cf. Jorion 2011: 7-8)

Above it has been mentioned that it is essential to identify risks. As its dynamic environment characterizes today's business world, new sources of risks emerge all the time. Therefore, a continuous identification procedure is essential to provide successful risk management.

Sources of risks can be identified in many ways. An approach considering risk categorization can improve the process of risk structuring. For instance, Jorion starts off categorizing risks by their level of perceptibility and distinguishes them by their likeliness to be known and to be considered within the risk assessment process. He labels the first category as the "known knowns," which can be assessed as being accurately definable and measurable risk factors, even though, losses can still occur due to the probability distribution of profit and loss. Further on, the classification named "known unknowns" considers weaknesses within the risk models, inaccurate measurement of volatilities and correlations as well as an incorrect mapping process. The third category describes the "unknown unknowns," which represent the occurrence of a scenario entirely out of scope, which are among others restrictions and governmental regulations. (cf. Jorion 2011: 7-8)

However, according to Dafir and Gajjala (2016), risks can be categorized by the nature or influence on firm-level performance.

Figure 1 illustrates the exposure of firm-level performance to the most recognized risk factors. Indeed, risk factors vary between individual firms as some might be exposed more or less to specific risk factors than others. Nevertheless, these elements named above solely represent a group of risks, whose dimensions also depend on the individual firm.

Figure 1: Risks influencing firm level performance
Source: own illustration after Dafir/Gajjala 2016

2.1 Risk Assessment

Risk Assessment considers the active process of recognizing and dealing with perils, as well as reducing them to a minimum in the best-case scenario.

The essentialities of the risk assessment process are shown via an example of the Health and Safety Executive UK, which has developed a procedure to recognize and assess possible endangers. The method considers five steps regarding the identification of the actual threat, as well as who might be affected. Moreover, these steps are reviewed, and proper measurements for risk mitigation are discussed. The entire process is documented thoroughly, as the risk assessment procedure requires regular reviewing. (cf. HSE UK)

The approach presumes the most critical stages of the risk assessment procedure. However, as the system enhances a certain complexity, the essential steps will be viewed in depth. Figure 2 below illustrates the general proceedings within risk assessment: Risk identification, risk analysis, and risk evaluation.

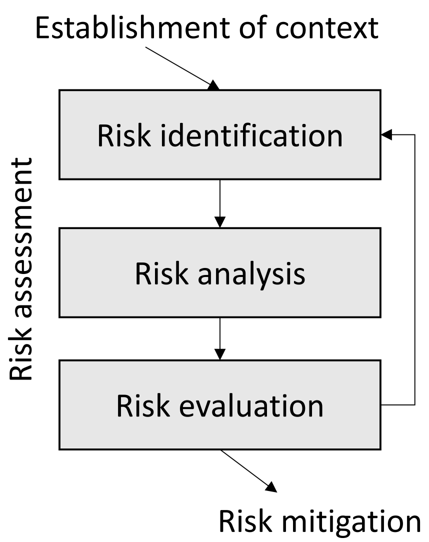


Figure 2: The Essentialities of the Risk Assessment Procedure
Source: own illustration after Möller et al. 2017

As it has already been mentioned above, risk identification is a continuous procedure and requires regular review due to the fast-changing economic environment and organizations being involved in various projects, markets, and countries (cf. Tchankova 2002: 293). It is essential for the entire risk assessment procedure to accurately identify the sources of risks as it builds the foundation for the following steps: Risk analysis, risk evaluation, and finally risk mitigation.

Risk analysis enhances a systematic and proactive approach, which encounters three stages: the identification of possible hazards as well as an analysis of frequencies and consequences. The frequency analysis understands the deductive investigation of incidences of endangers concerning a database, while the consequences analysis considers an inductive approach, which identifies every possible scenario derived from the potential hazards. (cf. IEC 60300-3-9 1995: 7)

Further on, different methodologies for risk analysis can be used: Qualitative risk analysis and quantitative risk analysis, noting that they are not contrary approaches but complement each other. Qualitative risk analysis focuses on risk identification as well as its characterization and estimation. It considers expert opinions and does not solely focus on numerical values. The quantitative approach assesses the immensity of the potential loss and the probability that this loss will eventually occur. Regarding the qualitative approach, methodologies as the scenario analysis, which encompasses the investigation of possible consequences arising from risks, as well as risk matrices, which use a ranking approach to identify the severity of a potential risk, are commonly used (cf. Möller et al. 2017: 461-471).

Regarding the quantitative risk analysis, the probability is the crucial factor in this mathematical approach as it measures uncertainty, which describes the lack of knowledge within a model. One of the most known tools within the field of quantitative risk analysis is the Monte Carlo Simulation, which implies the quantification of consequences for a probability distribution and its uncertainties (cf. Möller et al. 2017: 435-449).

Concerning risks regarding the financial markets, the approach of Value at Risk (VaR) is commonly used, as it considers "the quartile of the projected distribution of gains and losses over the target horizon" (Jorion 2001: 22). However, there should always be an interaction between qualitative and quantitative analysis to have a complete and broad view of the potential risk factors as it is of vital importance for the risk evaluation process. It is important that a standardized framework is adopted by companies in order to assess and quantify the level of risk. Therefore, VaR is a fundamental statistical technique that has been traditionally used by market participants to measure and ensure that market risk exposure are kept within limits in order to avoid intolerable losses. This statistical measure is expressed using three values: the amount of the potential loss, the probability of incurring this loss and the time frame. However, there are very few methods (Dafir/Gajjala 2016), that have been adopted to calculate VaR and these include:

- The historical method which uses statistical techniques to analyze losses based on past performance
- The variance method, which uses statistical analysis of returns, assuming that they are normally distributed based on the average return and standard deviation
- Monte Carlo simulations

The obtained results from the analytical part need to be judged and evaluated. Risk evaluation is undoubtedly subjective and always lies within the state and risk appetite of the organization (cf. Rausand

2013: 9). However, its purpose is of enormous importance as it finalizes the analysis and prepares for the decision-making process.

Concluding the risk assessment procedure, it can be stated that it may not encompasses many different steps. However, it implies a certain complexity due to only providing a raw framework, which is always in need of individualization.

2.2 Risk Mitigation

Based on the evaluated risk analysis, risk mitigation strategies are developed to minimize the severity of potential risks (cf. Rausand 2013: 55). However, risk mitigation is not applicable to all types of risks as mitigation strategies can only be applied to risks, whose source can be influenced by the organization at least to a certain extent. Considering the example from the financial market, an organization cannot affect the market itself, but it can, for instance, make use of derivatives as to mitigate the risk of volatile market prices.

2.3 Forecasting

The approach of forecasting considers the prediction of future events, which are based on the past (cf. Bowerman et al. 2005: 2-3), as it can be of great help regarding efficient and effective corporate planning (cf. Makridakis et al. 1998: 2).

Forecasting considers just as well as risk analysis a distinction between qualitative and quantitative forecasting methods. According to Makridakis et al. (1982), the selection of the process is based on the availability of quantitative information. If little or no quantitative information is provided, a qualitative approach might be used. Qualitative forecasting often encompasses a prediction, which is developed by a group of experts based on a question regarding the forecast. This is understood as the Delphi method. However, the technique of curve fitting, which contemplates matching the projection to an already given scenario, is quite popular as well. An appropriate example may be the product lifecycle, as many newly introduced products pass through this pattern. (cf. Bowerman et al. 2005: 8-10)

Regarding quantitative forecasting, different techniques can be applied. Generally, there is a distinction between extrapolative and causative techniques. The basis of the extrapolative method can be either of selective nature, which encompasses values observed at one point in time or of a serial character, which consists of a series of events within a specific time frame. Regarding the time series, the values, which are summed up in a dataset, are analyzed concerning identifying a pattern within the dataset. This pattern is considered to repeat itself in the same manner in the future. (cf. Song/Li 2008: 210) The literature distinguishes mostly among four different patterns. Concerning Bowerman et al., the components of a time series are named trend, cycle, seasonal variations, and irregular fluctuations.

As to identify the pattern, a moving average or weighted moving average can be used.

On the other hand, the causative technique regards the relationship of dynamic market structures by using tools like multiple regression analysis (cf. Tennent/Friend 2005: 85). Here, an independent variable representing forecasted value and a dependent variable, whose purpose is the criterion, are incorporated into a relation.

3 The Profit Cyclicality of the Airline Industry

The following section elucidates the main field of investigation – the airline industry and the profit cyclicality of the airline industry. The examination for reasons of the immense up- and downturns of the operating profits are based on the doctorate of Eva-Maria Cronrath. The investigation procedure is divided into four sub-chapters starting off with the external environment, moving on to the industry itself and narrowing it down to the business factors. In the end, there will be a focused descriptive analysis of the risk factors presenting the airline industry as the input variables for the primary model are derived from there.

As the airline industry has been growing since almost the beginning of its existence, it is quite astonishing that the yearly average operating profit of the industry accounts to zero. This is due to enormous ups and downturns, whose amplitudes become more severe with every year passing by. Further on, this phenomenon can be observed throughout the entire world, whereas some geographical regions are performing better in terms of having smoother profit cycles than others. The same accounts for individual businesses. Therefore, it can be concluded that there is a variance of factors which influence this occurrence. (cf. Cronrath 2018: 1-6)

3.1 Exogenous Factors

The airline industry is influenced by exogenous factors, which are independent of the industry and individual businesses and cannot be influenced but by the entire economy. The most relevant factor is demand, which is determined by the development of the Gross Domestic Product (GDP) and the growth rate of the population, as it determines a businesses' need to supply (cf. Lyneis 2000: 7). Further on, it is significant to consider the current state as well as the development of politics and other extraordinary occurrences, as it may have a drastic impact on the businesses' operations. Due to an increase of terrorist attacks in the past, the International Air Transport Association (IATA) has published estimation of the impact of terrorist attacks in western Europe, which considers a reduction of air passenger traffic in the period from end 2015 to early 2016 (cf. Oaxley 2017). However, events like these cannot be predicted nor considered in the forecasting procedure, but solely be reacted upon as quickly as possible. Moreover, the volatility of jet fuel prices is regarded as another exogenous factor, which influences the airline industry, as it accounts to a large proportion of an airline's operating costs and is strongly affected by price swings (cf. Dafir/Gajjala 2016: 32).

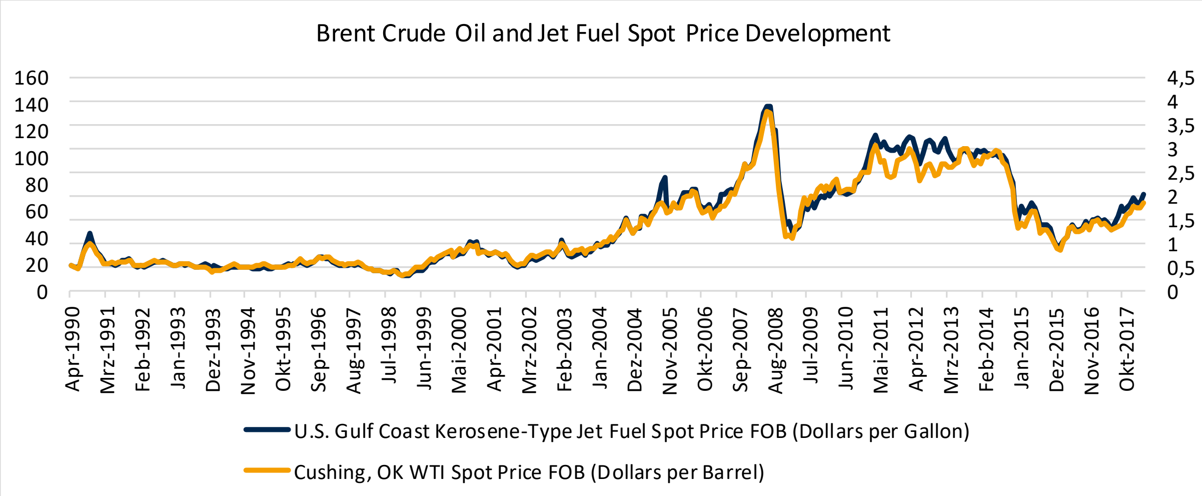


Figure 3: The Development of the monthly average Spot Prices of Crude Oil and Jet Fuel
Source: U.S. Energy Information Administration 2018

The volatility of jet fuel spot prices, which moves in the same behavioral pattern as the spot price of crude oil, can be observed in Figure 3. The closely related movements can be traced back to the oil market itself, as jet fuel only makes up a small proportion of the oil market and airlines do not consume enough to influence the market price in any kind. Referring to the U.S. Energy Information Administration (2017), the daily consumption of jet fuel makes up only 8% of the entire daily oil consumption in the US. Hence, the reasons for the large price swings account the same as for any publicly traded commodity, as supply, demand, and politics strongly influence them. However, airlines have several possibilities to reduce their exposure regarding the price volatility as it is not always feasible to pass on the additional costs to the passengers due to the arising time lag between the ticket purchase and the purchase of fuel for the respective flight (cf. Lim/Hong 2014). On the one hand, they can enter long-term contracts with fixed prices with suppliers and on the other hand they can make use of financial instruments regarding forward or future contracts as well as derivatives, which consider options, collars, and swaps (cf. Morrell/Swan 2006: 713-725).

3.2 Industry Factors

Respecting the market structure, which considers the airline industry as solely one participant, it is crucial to recognize that the market is still regulated by the respective governments, even though liberalization has taken place to a significant extent. However, the regulation intends to avoid destructive competition due to the microeconomic phenomenon of the empty-core within the airline industry. Organisation theories and the various stream of strategy theory such as inter-firm rivalry, multipoint competition and tacit collusion and the groundwork of game theory (Fundeberg/Tirole1995), have been used to explain firm level interaction and the airline industry is no exception. The application of game theory to illustrate industry and firm level behaviour is deemed to be one of the most influential theoretical tools when observing the competitive behaviour of firms. Regarding the game theory, a core is empty when an alternative can outbid each coalition and therefore results in no stable solution (cf. Button 2003: 7-8). Concluding, airlines are not able to compete on seats but on ancillary services provided to the customer, which could make up an airline's unique selling proposition (cf. Tretheway/Markhvida 2014: 10).

Further on, other participants of the air transport industry need to be reviewed, as they form the aviation value chain, which is illustrated below in Figure 4 along with the airline industry.

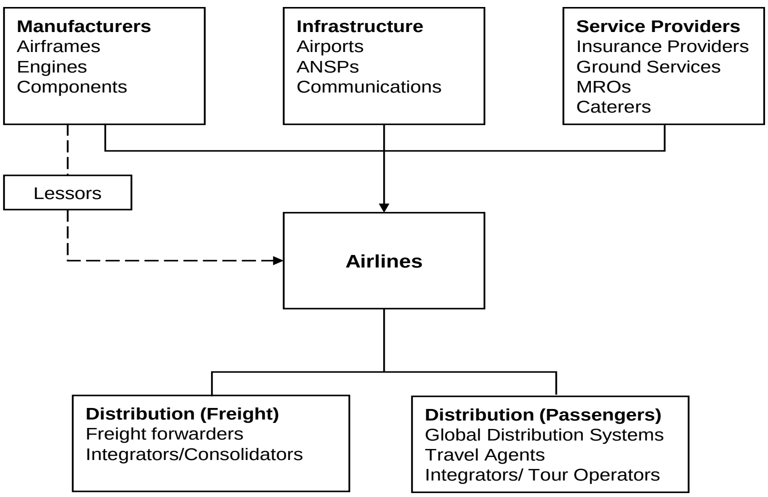


Figure 4: The Aviation Value Chain
Source: own illustration after Tretheway/Markhvida 2014

The upstream sector of the aviation value chain considers manufacturers, infrastructure, and other service providers, while the downstream sector consists of the distribution of either freight or passengers. Regarding the perspective of airlines, the supplying participants of the aviation value chain influence an airline's operations heavily, as they need to consider among others lead times from aircraft manufacturers, as well as infrastructure management and organization at airports. Still, it is to recognize that the airline industry has the highest capital investment along the value chain, which can be observed below in Figure 5.

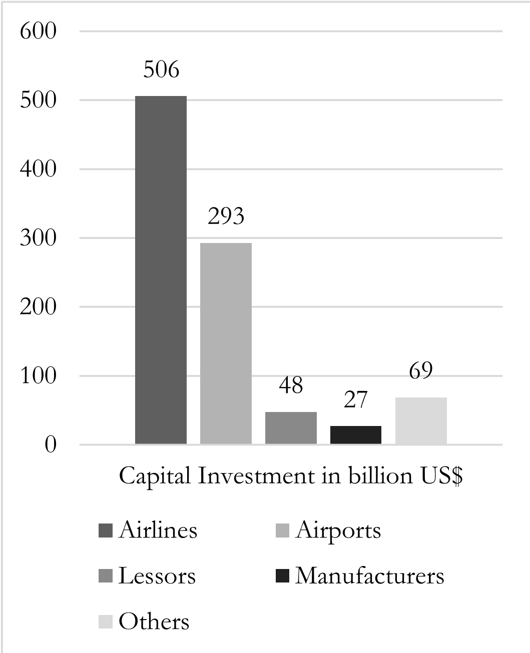


Figure 5: Capital investments along the Aviation Value Chain
Source: own illustration after IATA 2011

Capital investments within the airline industry amount to 53% of the entire aviation value chain, which is mostly due to capital-intensive assets like aircraft, maintance, repairs and overhaul (MRO) ground equipment and other corporate resources (cf. Tretheway/Markhvida 2014: 6-7). However, the question arises if there is any return regarding the invested capital. This can be viewed via the economic profit, which comprises the return on capital employed exceeding the cost of capital. Considering a study of Wojahn (2012), who assessed the economic profit of 69 publicly listed airlines from 1981 to 2010, it can be observed that there have been financial losses for nearly 20 years. Nevertheless, airlines keep investing regardless of capacity utilization.

3.3 Business Factors

All passenger airlines offer the same product: The service of transporting people from one destination to another (cf. Budd/Ison 2016: 108), which makes it a non-durable product. Therefore, differentiation takes place via the strategic orientation – the business model. Full-Service Network Carriers, Low-Cost Carriers, Regional Carriers, Charter Carriers, and Hybrid Carriers face different challenges within the industry. However, one of the essential difficulties regarding the business is found within airline capacity management, as it is a significant driver of the profit cyclicality based on the findings of Cronrath (2018).

The illustrated model in Figure 6 outlines the influencing dynamics of airline flight schedules, which makes up capacity management, regardless of influencing factors on the part of other members of the aviation value chain. According to Barnhart et al. (2012), the airline flight schedule is affected by the following dynamics – demand, pricing, and schedule design and performance, which stimulate each other as well. For a better understanding of the interrelations of the influencing dynamics, an individual consideration may follow.

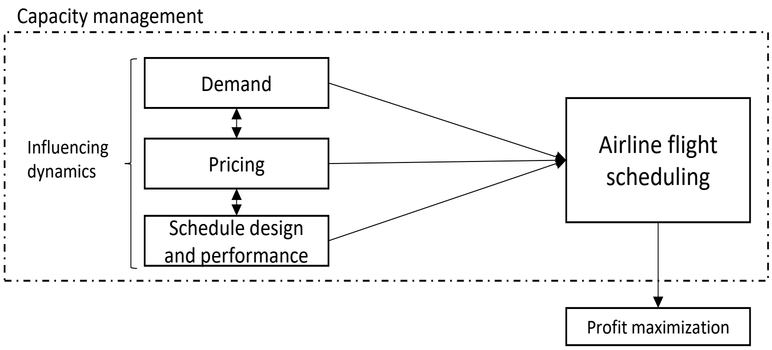


Figure 6: The Dynamics of Airline Capacity Management
Source: own illustration after Barnhart et al. (2012); Ball et al. (2010)

Demand is the essential driver for business operations, as it expresses the wish or need for consumption of a product or service. In the airline industry, air travel demand is assessed by evaluating origin-destination market (O-D market), but not for a flight leg in an airline network. It is measured by the potential flow per period in one or both directions of an O-D market. (Barnhart et al. 2009: 55–56) However, predicting future demand becomes difficult due to various stimulating factors. Besides macroeconomic factors regarding the evolution of population or the development of the gross domestic product, the level of service impact on behalf of the airline along with its pricing and frequency policy influence the rate of demand (cf. Suryani et al. 2010: 2328). According to Gillen et. al (2008), this results in an elastic demand regarding price and time elasticity, whereby it needs to be distinguished between business and leisure travelers. Nevertheless, the estimation of future demand is fundamental for business decisions as among others, for capacity forecasting.

The component pricing is part of an airlines' yield management and hence, drives revenue and profits. In the research literature, three main approaches are discussed to determine the price for an airfare: The classical marginal costs pricing, the demand-based pricing, and the service-based pricing.

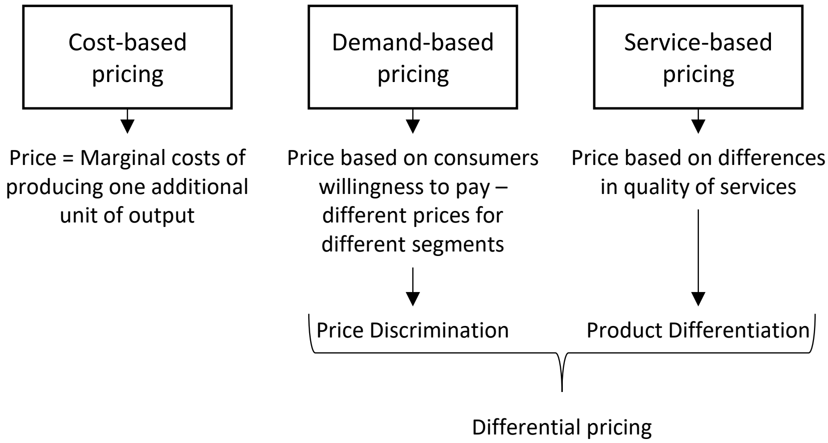


Figure 7: The Derivation of the traditional Fare Pricing Approach
Source: own illustration after Barnhart et al. (2009)

In Figure 7 the derivation of the traditional fare pricing approaches is illustrated, which are commonly used within the airline industry. Differential pricing combines the approach of demand-based pricing and service-based pricing. While demand-based pricing incorporates consumers' willingness to pay into its pricing scheme via setting different prices for different segments with the aim to maximize profits, service-based pricing considers prices based on the quality of service as the differentiation in price between a "first class" seat and an "economy" seat, as the perceived quality in service deviates. Hence, the differential pricing method approaches price setting from two dimensions as to offer a variety of product options to the customer who must make a compromise between restricted low fares and unrestricted high fares (cf. Barnhart et al. 2009: 75-79). Overall, this may lead to improved revenue. Therefore, pricing is considered a dynamic influencer due to its direct stimulation of demand on behalf of the airline itself.

Differential pricing combines the approach of demand-based pricing and service-based pricing. While demand-based pricing incorporates consumers' willingness to pay into its pricing scheme via setting different prices for different segments with the aim to maximize profits, service-based pricing considers prices based on the quality of service as the differentiation in price between a "first class" seat and an "economy" seat, as the perceived quality in service deviates. Hence, the differential pricing method approaches price setting from two dimensions as to offer a variety of product options to the customer who must make a compromise between restricted low fares and unrestricted high fares (cf. Barnhart et al. 2009: 75-79). Overall, this may lead to improved revenue. Therefore, pricing is considered a dynamic influencer due to its direct stimulation of demand on behalf of the airline itself.

The third influencing dynamic viewed in Figure 6 regards airline schedule design and performance. Beforehand, it needs to be stated that proper schedule design and development requires a given set of routes in operation as well as a fleet of aircraft. Based on this information, schedule design can be performed by focusing on the following elements: frequency planning, timetable development, fleet assignment, and aircraft rotation planning (cf. Barnhart et al. 2009: 175). In this case, frequency planning considers how often an airline operates flights on a specific route. This is of essential importance, as frequency may stimulate demand to a certain extent and it makes up amongst others an airline's market share on a specific route (cf. Tretheway 2004: 4). Also, the timetable development has a stimulating effect on demand and particularly on demand of business passengers, as they care for a departure time, which is in accordance with their schedules. Fleet assignment, which regards the decision on the type of aircraft used for individual departure times, is a further element of the airline schedule design. It is performed to make efficient use of the aircraft fleet by not causing additional costs caused by unutilized capacity on a specific route or missing out on additional revenue due to higher demand than the available capacity of an aircraft on a distinctive route (cf. Barnhart et al. 2012: 146-148). The last element reviews aircraft rotation planning, which requires the scheduling of the frequency of use of an aircraft and its alignment with maintenance regulations.

After elucidating the influencing dynamics on airline flight planning, the complexity of capacity management and hence, of capacity forecasting becomes visible. However, diligent execution of this process is of significant importance to ensure an airline's overall performance.

3.4 Risk Factors

As already elaborated in the earlier sections of this paper, the airline industry is exposed to various risks regarding its external environment, industry, operations, financial operations and service reputation. In the literature, risks of the airline industry are not explicitly identified, but how risk management and particularly the application of risk mitigation measures is approached. Therefore, annual reports of 10 airlines, which belong to the largest airlines in the world, have been reviewed to obtain the most relevant specific risks within the airline industry.

Resuming the risk factors listed in Table 1, an enormous similarity of the named risk factors can be observed, and differences can solely be made between the different business models. Further on, a clear distinction between qualitative and quantitative risks can be derived. In Figure 8, a summary of the most relevant risks is presented. A structure is considered, which distinguished between qualitative and quantitative risks as well as classification by nature.

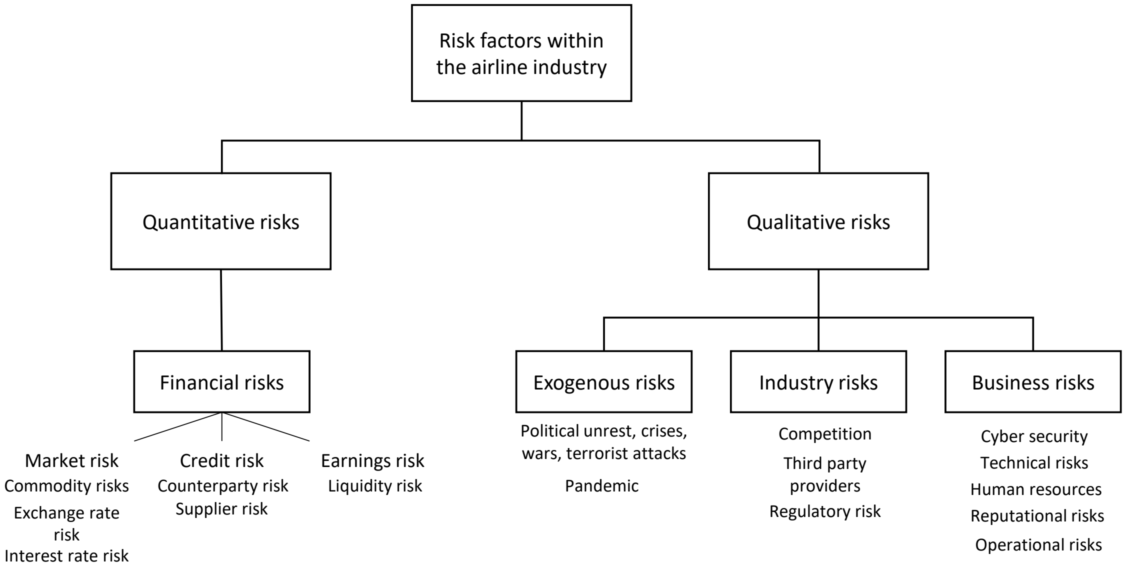


Figure 8: *Summary of main Risk Factors within the Airline Industry*
Source: *own illustration after the annual reports of Air France - KLM (2018), China Southern Airlines Company Limited (2018), DELTA Air Lines (2018), Deutsche Lufthansa AG (2018), Easy Jet Airline Company Limited (2018), International Consolidated Airlines Group S.A. (2017), Ryanair DAC (2018), Southwest Airlines Co. (2018), Turkish Airlines (2017), and UNITED Continental Holdings (2017)*

Below, Table 1 lists the reviewed airlines and the risks they are exposed to according to their annual report.

Table 1: Identified risks of a choice of airlines belonging to the largest stock listed airlines in the world according to either revenue or passenger traffic

Airline	**Possible risk factors**			
Deutsche Lufthansa AG	*Quantitative risks:* • Fuel price movement • Exchange rate movement • Earnings risk • Loss of investment grade rating	• Breaches of compliance requirements • Exchange rate losses on pension funds • Credit risks	*Qualitative risks:* • Cyber risks • Pandemic diseases • Flight operations risks • Human resources	• Crises, wars, political unrest or natural disasters • Market entry OEM • Contaminated foods
Turkish Airlines	*Financial risks:* • Cash flow risks • Commodity price risk • Interest rate risk	• Foreign currency rate risk • Other party risk		
Ryanair DAC	*Risks related to Company:* • Changes in fuel costs • Cyber security risks • Currency fluctuations	• Credit risks • Human resources • Legal risks • Regulatory risks	*Risks related to airline industry:* • Pandemic diseases • Natural disasters • Airline Industry Margins	
United Continental Holdings, Inc.	*Risk factors:* • Political crises, wars, unrest, terrorist attacks • Cybersecurity	• Technical risks • Counterparty risks • Supply risks	• Reputational risks • Commodity risks • Human resources	• Pandemic diseases • Regulatory risks • Liquidity risks
International Consolidated Airlines Group S.A	*Strategic:* • Airports and Infrastructure • Brand reputation • Competition • Consolidation and deregulation • Digital disruption • Government intervention	*Business and operational:* • Cyber security • Technical risk • Human resources • Political and economic conditions	*Financial:* • Debt funding • Financial risk • Tax	*Compliance and regulatory:* • Group governance structure • Non-compliance with key regulation including competition, bribery and corruption law
DELTA Air Lines, Inc.	*Risk factors*: • Political crises, wars, unrest, terrorist attacks • Cyber security	• Technical risks • Regulatory risks • Foreign currency risk	• Reputational risks • Commodity risks • Human resources	• Pandemic diseases • Liquidity risks • Interest rate risk

Table 1 continued

Air France-KLM	*Risks related to the air transport activity:* • Seasonal nature of the industry • Cyclical nature of the industry • Trend in oil price	• Terrorist attacks, threats of attack, geopolitical instability • epidemics • Regulatory risk • Operational risks	*Risks linked to the groups activity:* • Cyber security • Compliance risks • Legal risks • MRO risks • Currency risk • Interest rate Risk	• Fuel price risk • Counterparty risk • Equity risk • Liquidity risk • Financing risk • Investment risk
Southwest Airlines Co.	*Risk factors:* • Political crises, wars, unrest, terrorist attacks	• Cyber security • Technical risks • Regulatory risks	• Commodity risks • Human resources • Pandemic diseases	• Liquidity risks • Competition
Easy Jet Airline Company Limited	*Principal risk and uncertainties:* • Major safety incident • Security threat or attack • Competition, capacity, and • Industry consolidation	• Significant network disruption • Third party service provider • Industrial action • Single fleet risk • Financial risk	• Compliance risk • Regulatory risk • Legal risk • Cyber security • Reputational risk	
China Southern Airlines Company Limited	*Macro environment risks:* • Risks of fluctuation in macro-economy • Risks of macro policies	*Industry risk:* • Risk of intensified competition • Competition from other modes of transportation	*Risk of company management:* • Safety risk • Risk of high capital • Expenditure	*Financial risk of the company:* • Foreign currency risk • Jet fuel price Risk

Source: *Annual Reports of Air France - KLM 2018, China Southern Airlines Company Limited 2018, DELTA Air Lines 2018, Deutsche Lufthansa AG 2018, Easy Jet Airline Company Limited 2018, International Consolidated Airlines Group S.A. 2017, Ryanair DAC 2018, Southwest Airlines Co. 2018, Turkish Airlines 2017, and UNITED Continental Holdings 2017*

4 Dynamic risk assessment

The dynamic risk assessment process considers the integration of the system dynamics methodology into the classical risk assessment process, which consists of risk identification, risk analysis, and risk evaluation. Referring to the literature review, the components of capacity management have been discussed but solely regarding the airline industry and its passengers. However, in Figure 9 the interrelation of airlines and other participants of the aviation value chain are illustrated to encompass the dynamics of capacity management fully. The figure clarifies the interdependencies of the individual participants regarding supply and demand as well as their direct impact on airline capacity management. Specifically, the impact of original engine manufacturers (OEMs) and airports are highlighted in red within Figure 9. Regarding the effect of OEMs, airlines need to consider long lead times when planning capacity addition through ordering of aircrafts. Furthermore, lead times may extend unexpectedly from time to time. Hence, the relationship of OEMs and airlines needs to be assessed sensitively and respected in particular within flight scheduling (cf. Mack et al. 2013: 16). Concerning the relationship of airlines and airports, airlines have to design the flight schedule in accordance with the airports slot capacity. Moreover, the distribution of flight slots is accounted as highly competitive depending on the airport and the approached route (cf. Barnhart et al. 2012: 143). Therefore, the scope of airline capacity forecasting does not solely relate to internal aspects, but further needs to involve the capacity of other participants of the aviation value chain.

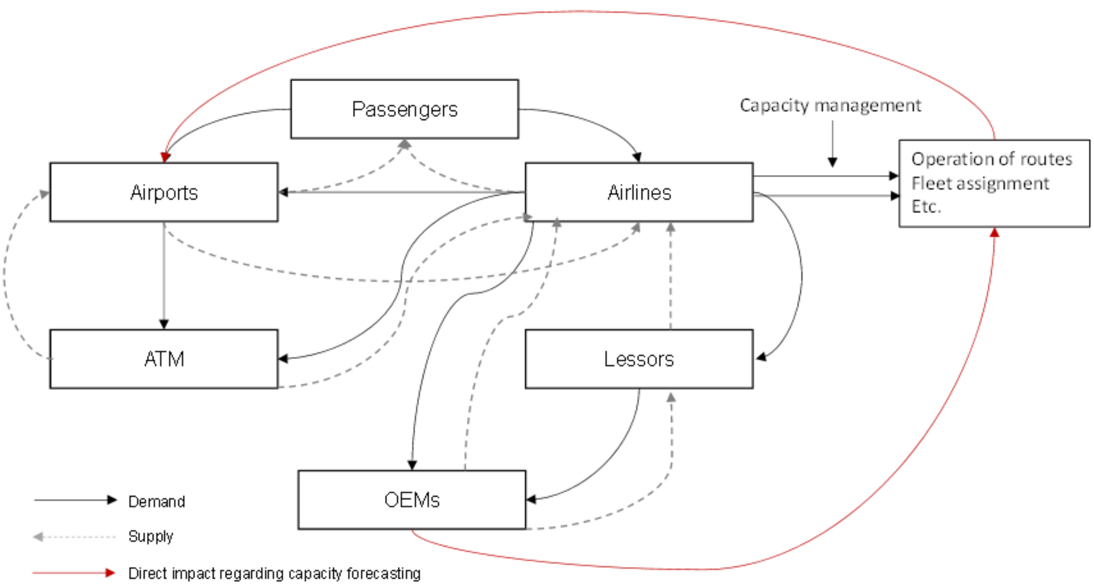


Figure 9: The Supply-Demand Balance within the Airline Industry

Source: *own illustration*

In Figure 10 the context of capacity forecasting, which has been elaborated in the previous sections of this paper is associated with the risk of fuel price volatility (commodity risk) through further internal business factors regarding costs and revenue. The black lines indicate the relationship of the individual factors, which have been assessed through the literature review. However, the thesis aims to investigate the direct impact of risks on capacity management. The research interest is marked through the dotted line in Figure 10 and encompasses the assessment of the direct impact of commodity risk on capacity forecasting. As risks have not been considered yet in capacity forecasting it would close a gap within the currently existing literature.

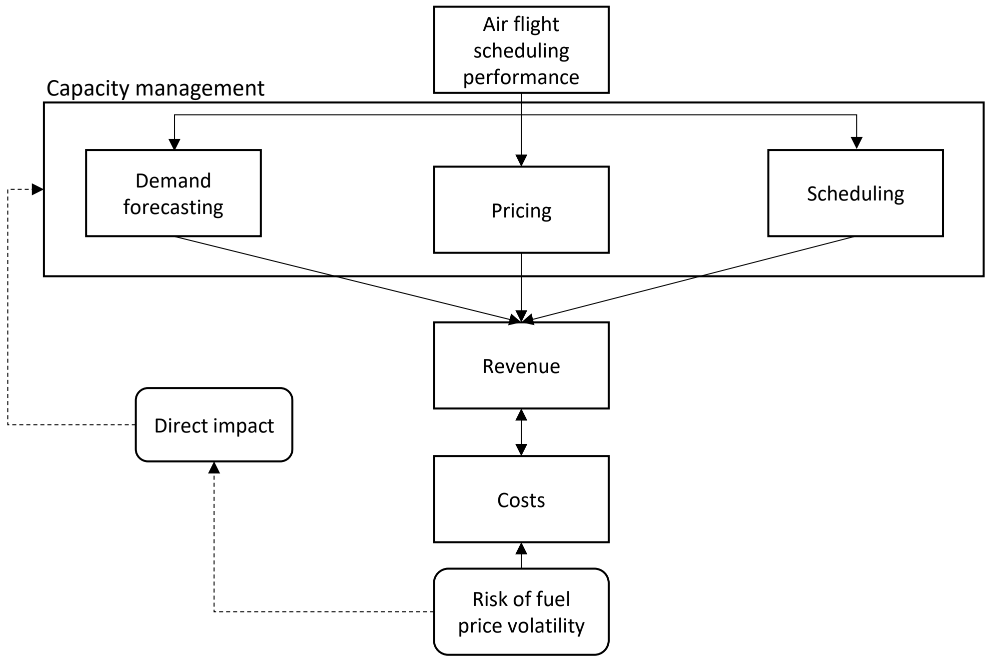


Figure 10: The direct Impact of Risks on Airline Capacity Management
Source: own illustration

4.1 Risk Identification

As it can be derived from the literature review, specific risks regarding the airline industry have already been identified. However, the thesis focuses solely on the impact of quantitative risks due to measurability. Nevertheless, it is essential to carry out a regular review of the risk identification process.

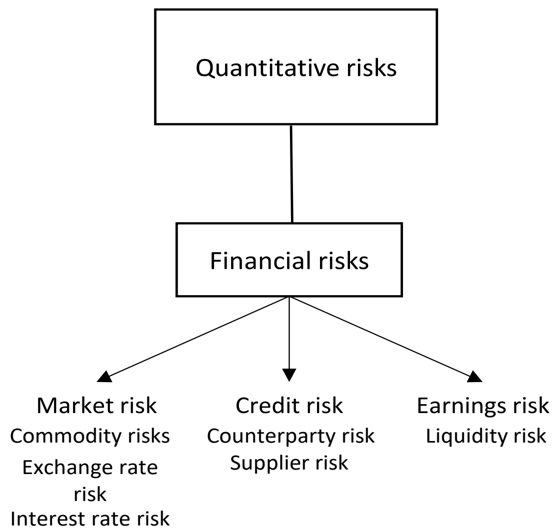


Figure 11: Quantitative Risks within the Airline Industry
Source: own illustration

The risks indicated in Figure 11 are considered as the most relevant quantitative risks factors to which airlines are exposed. However, this investigation will focus on one risk factor – the risk of fuel price volatility.
Reasoning the choice of risk factor and having a better understanding of the risk factors' background, a reflection of the risk of jet fuel price volatility will follow.
According to the economic performance analysis of the airline industry for the year 2017 of IATA, 18.8% of airlines' annual operating costs amount to fuel cost, which represents a decrease of 1.8% compared to the proportion of airlines' fuel costs in 2016. However, IATA forecasts a further increase in the proportion of fuel costs amounting to 20.5%, as the forecast predicts an increase in fuel usage as well as in fuel prices. The increase in fuel usage is mainly on behalf of the airline itself and driven by various factors regarding among others traffic, the fuel efficiency of aircraft, and inefficiencies of aerospace and airports, which lead to a waste of fuel burn of around 5% each year. (cf. IATA Economics 2017: 4) However, the jet fuel price is influenced differently. Jet fuel is solely a refined product of crude oil, hence, the price for jet fuel follows the price trend of crude oil, as it has been aforementioned. Thus, the drivers of the crude oil price need to be identified. Crude oil is traded on the commodity market, and prices are controlled by traders, who bid on future contracts, which explains the daily fluctuating changes in the crude oil spot price. However, exogenous forces affect the bidding behaviour of the traders.
In Figure 12 the stimulating factors, which affect the crude oil price, are presented. It is narrowed down to the availability of supply, demand, and future demand. Nevertheless, these can be massively affected by political crises and natural hazards. Referring to an example of the civil war in Libya along with the rise of political unrest in the northern African countries in March 2011 – the Arab spring, the crude oil spot price increased by $15 per barrel between February 18th and March 5th, due to a loss in supply of around 1.5 million barrels per day from Lybia (cf. U.S. Energy Information Administration 2012). The loss along with the overall unstable political situation, directly affected supply and thus, the bidding decisions of the traders.

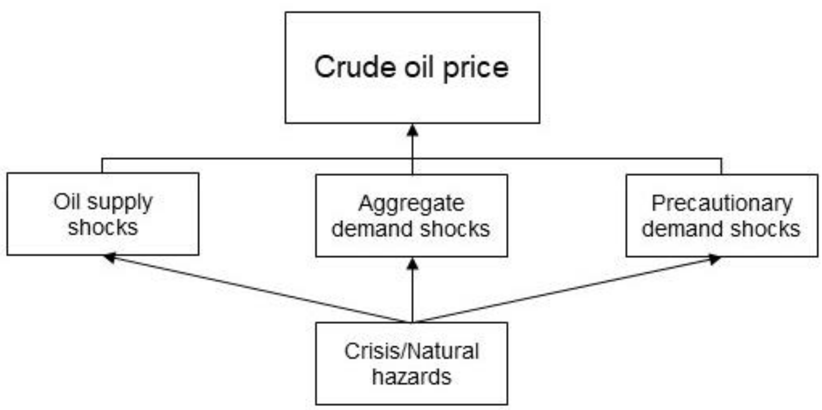


Figure 12: The stimulating Factors of the Crude Oil Price
Source: Author´s own illustration after Kilian (2009)

4.2 Risk Analysis

The risk analysis considers the construction of the model via the system dynamics approach in the same matter as it has been described in the previous sections above. Therefore, it starts off with explaining the actual problem and moves on to defining a dynamic hypothesis, which is developed from the base model in its first state. After that, the base model is advanced further along with translating it into the equivalent equations, which will be tested and compared to a given dataset to provide validation. In the end, an evaluation of results will take place. In Part 2 of this extended paper risk analysis is adopted through empirical testing by observing volatility of crude oil prices and impact on airlines.

5 Conclusion

This paper has introduced 2 parts, the first part solely examines the literature on risk management and the second part has attempted to incorporate the establishment of a dynamic airline forecasting model based on the influencing dynamics regarding demand assessment, pricing of airfares, as well as flight-scheduling, which have been determined through an extensive literature review. Evidently risk management is a key component on how organizations can adopt ways to mitigate risks which may undermine firm level performance, Within the context of the airline industry exogenous factors were evaluated and also paying ample attention to other risks related to financial performance of a firm. The second part of this paper focuses on the modelling side of systems forecasting.

References

Air France - KLM (2018): Registration Document 2017. Including the Annual Financial Report. (http://www.airfranceklm.com/sites/default/files/publications/ddr_air_france-klm_2017_va_0.pdf). Accessed on 21.01.2021.

Ball, M.; Barnhart, C.; Dresner, M.; Hansen, M.; Neels, K.; Odoni, A. et al. (2010): Total Delay Impact Study. A Comprehensive Assessment of the Costs and Impacts of Flight Delay in the United States.

Barnhart, C.; Belobaba, P.; Odoni, A. (2009): The Global Airline Industry. [Elektronische Ressource], Chichester : Wiley; American Institute of Aeronautics and Astronautics, Inc. (Aerospace Series, vol. 23).

Barnhart, C.; Fearing, D.; Odoni, A.; Vaze, V. (2012): Demand and capacity management in air transportation. In: EURO Journal on Transportation and Logistics, 1. (2012), No. 1-2, pp. 135-155.

Bowerman, B. L.; O'Connell, R. T.; Koehler, A. B. (2005): Forecasting, time series, and regression. An applied approach. 4. ed., Belmont, CA. : Thomson Brooks/Cole (Duxbury applied series).

Budd, L.; Ison, S. (2016): Air Transport Management. An international perspective. Milton : Taylor and Francis.

Button, K. (2003): Does the theory of the 'core' explain why airlines fail to cover their long-run costs of capital? In: Journal of Air Transport Management, 9. (2003), No. 1, pp. 5-14.

China Southern Airlines Company Limited (2018): Annual Report 2017. (https://www.csair.com/en/about/investor/yejibaogao/2018/resource/d3a41612260b0cc0cf4482c45f7e8cb3.pdf). Accessed on 21.01.2021.

Cronrath, E.-M. (2018): The airline profit cycle. A system analysis of airline industry dynamics. Abingdon, Oxon, New York, NY : Routledge (Routledge studies in transport analysis, vol. 8).

Dafir, S. M.; Gajjala, V. N. (2016): Fuel hedging and risk management. Strategies for airlines, shippers and other consumers. Hoboken : Wiley (The wiley finance series).

DELTA Air Lines (2018): Annual Report 2017. (http://d18rn0p25nwr6d.cloudfront.net/CIK-0000027904/2658ec39-e92c-4293-b169-3402bd20acdd.pdf). Accessed on 21.01.2021.

Deutsche Lufthansa AG (2018): Annual Report 2017. (https://investor-relations.lufthansagroup.com/fileadmin/downloads/en/financial-reports/annual-reports/LH-AR-2017-e.pdf). Accessed on 21.01.2021.

Easy Jet Airline Company Limited (2018): Annual Report and Accounts 2017. (http://corporate.easyjet.com/~/media/Files/E/Easyjet/pdf/investors/results-centre/2017/2017-annualreport-and-accounts-v1.pdf). Accessed on 21.01.2021.

Ebersoll, M.; Stork, F. (2016): Smart Risk Assessment. Effiziente Risikoidentifizierung und -bewertung. Berlin : Erich Schmidt Verlag.

Gillen, D. W.; Morrison, W. G.; Stewart, C. (2008): Air Travel Demand Elasticities: Concepts, Issues and Measurement (https://www.fin.gc.ca/consultresp/airtravel/airtravStdy_2-eng.asp#4.). Accessed on 25.04.2018.

HSE UK: Risk Management. How do I do a risk assessment? (http://www.hse.gov.uk/risk/faq.htm#q1). Accessed on 08.03.2018.

IATA (2011): Vision 2050. (https://www.iata.org/contentassets/bccae1c5a24e43759607a5fd8f44770b/vision-2050.pdf). Accessed on 21.01.2021.

IATA Economics (2017): Economic performance of the airline industry (http://www.iata.org/publications/economics/Reports/Industry-Econ-Performance/IATA-Economic-Performance-of-the-Industry-end-year-2017-report.pdf). Accessed on 01.05.2018.

IEC 60300-3-9 (ed.) (1995): Dependability Management-Application Guide: Risk Analysis of Technological Systems. Geneva :

International Consolidated Airlines Group S.A. (2017): Annual Report 2016. (http://www.iairgroup.com/phoenix.zhtml?c=240949&p=irol-reportsannual). Accessed on 03.05.2018.

Jorion, P. (2001): Value at risk. The new benchmark for managing financial risk. 2. ed., New York : McGraw-Hill.

Jorion, P. (2011): Financial risk manager handbook plus test bank. FRM Part I/Part II. 6. ed., Hoboken, NJ : Wiley (Wiley finance).

Kilian, L. (2009): Not All Oil Price Shocks Are Alike. Disentangling Demand and Supply Shocks in the Crude Oil Market. In: American Economic Review, 99. (2009), No. 3, pp. 1053-1069.

Lim, S. H.; Hong, Y. (2014): Fuel hedging and airline operating costs. In: Journal of Air Transport Management, 36. (2014), pp. 33-40.

Lyneis, J. M. (2000): System dynamics for market forecasting and structural analysis. In: System Dynamics Review, 16. (2000), No. 1, pp. 3-25.

Mack, R.; Jiang, H.; Peterson, R. M. (2013): A Discussion of the Capacity Supply. Demand Balance within the Global Commercial Air Transport Industry. (http://www.boeing.com/resources/boeingdotcom/commercial/about-our-market/assets/downloads/AirTransportCapacitySupplyDemand-Balance.pdf). Accessed on 21.01.2021.

Makridakis, S. G.; Wheelwright, S. C.; Hyndman, R. J. (1998): Forecasting. Methods and applications. 3. ed., Hoboken, NJ : Wiley.

Möller, N.; Ove Hansson, S.; Holmberg, J.-E.; Rollenhagen, C. (2017): Handbook of Safety Principles. Hoboken, NJ : Wiley.

Morrell, P.; Swan, W. (2006): Airline Jet Fuel Hedging. Theory and Practice. In: Transport Reviews, 26. (2006), No. 6, pp. 713-730.

Oaxley, D. (2017): Estimating the impact of recent terrorist attacks in Western Europe (http://www.iata.org/publications/economics/Reports/European-terrorism-impact.pdf). Accessed on 01.04.2018.

Rausand, M. (2013): Risk Assessment. Theory, Methods, and Applications. Hoboken : Wiley (Statistics in Practice).

Ryanair DAC (2018): Annual Report 2017. (https://investor.ryanair.com/wp-content/uploads/2017/07/Ryanair-FY2017-Annual-Report.pdf). Accessed on 21.01.2021.

Samunderu, E. (2016): Cross-platform network migration of airline business model: A signal of the "new game" hybrid model. Evidence from Air Berlin's performance metrics. In: Research Journal for Applied Management, 3. (2016), No. 1, pp. 85-112.

Song, H.; Li, G. (2008): Tourism demand modelling and forecasting—A review of recent research. In: Tourism Management, 29. (2008), No. 2, pp. 203-220.

Southwest Airlines Co. (2018): 2017 Annual Report to Shareholders. (http://investors.southwest.com/~/media/Files/S/Southwest-IR/Bookmarked%20Annual%20no%20blanks.pdf). Accessed on 21.01.2021.

Suryani, E.; Chou, S.-Y.; Chen, C.-H. (2010): Air passenger demand forecasting and passenger terminal capacity expansion. A system dynamics framework. In: Expert Systems with Applications, 37. (2010), No. 3, pp. 2324-2339.

Tchankova, L. (2002): Risk identification – basic stage in risk management. In: Environmental Management and Health, 13. (2002), No. 3, pp. 290-297.

Tennent, J.; Friend, G. (2005): Guide to business modelling. 2nd ed., London : Profile (The Economist books).

Tretheway, M. W. (2004): Distortions of airline revenues. Why the network airline business model is broken. In: Journal of Air Transport Management, 10. (2004), No. 1, pp. 3-14.

Tretheway, M. W.; Markhvida, K. (2014): The aviation value chain. Economic returns and policy issues. In: Journal of Air Transport Management, (2014), No. 41, pp. 3-16.

Turkish Airlines (2017): Annual Report 2016. (http://investor.turkishairlines.com/documents/ThyInvestorRelations/THY_2016_ANNUAL_REPORT-v2.pdf). Accessed on 21.01.2021.

U.S. Energy Information Administration (2012): 2011 Brief: Brent crude oil averages over $100 per barrel in 2011 (https://www.eia.gov/todayinenergy/detail.php?id=4550). Accessed on 21.01.2021.

U.S. Energy Information Administration (2017): Crude Oil and Petroleum Products (https://www.eia.gov/energyexplained/index.php?page=oil_use). Accessed on 27.05.2018.

U.S. Energy Information Administration (2018): Monthly Spot Prices of Petroleum and other liquids (https://www.eia.gov/dnav/pet/pet_pri_spt_s1_m.htm). Accessed on 04.04.2018.

UNITED Continental Holdings (2017): Annual Report. (https://ir.united.com/static-files/f8f2f775-021e-44a0-aa6d-02ec9626d257). Accessed on 21.01.2021.

Waite, M. (ed.) (2012): Paperback Oxford English dictionary. 7. ed., Oxford : Oxford University Press.

Wojahn, O. W. (2012): Why does the airline industry over-invest? In: Journal of Air Transport Management, (2012), No. 19, pp. 1-8.

Authors

Prof. Dr Eyden **Samunderu** is a leading expert and trusted advisor in the area of air transport with extensive consulting experience at senior level. He currently holds a PhD in Strategic Management and is a Program Director at the International School of Management (ISM) in Dortmund Germany. He is also a Managing Partner at AMENA Africa Ltd and Board Advisor at Aviation Partners Africa [APA] London. His research interests include: air transport economics, multimarket contact, strategic group theory, competition dynamics, container logistics and maritime economics.

Yvonne **Küpper** is an Analyst at Innogy SE Dortmund focusing on Credit Risk Management. Her areas of research interest include air transport finance and risk management.

Samunderu, Eyden; Küpper, Yvonne

Testing the impact of commodity risk on airline capacity forecasting: A systems dynamic framework from an airline perspective: An empirical analysis – Part 2

Received 19.08.2020 · Received in revision 17.11.2020 · Accepted 22.01.2021

Abstract

This paper adopts an empirical method of testing commodity risk on airline capacity forecasting. The paper incorporates modelling of a capacity-forecasting model through the adoption of systems dynamics. The paper attempts to explore and test the impact of commodity risk by analyzing the effect of changes in jet fuel spot price on average airfares of US domestic market. The study also attempts to measure the impact of other interrelated capacity variables. The postulated hypotheses have been derived from capacity risk analysis and causal feedback loop logic that underlines the study to observe the interrelations of capacity and risk variables in a dynamic setting.

Keywords: Capacity forecasting, Risk assessment, risk mitigation, systems dynamics, jet fuel spot price and profit cyclicality, capacity variables, average fares, feedback loop

1 Introduction

Modelling incorporates the testing of the hypotheses via a dynamic risk assessment model. The methodology of system dynamics considers the deconstruction process of complex problems via decomposing all variables, which might influence the problem, into an interrelated network (cf. Sterman 2000).

2 The System Dynamics Approach

The methodology of system dynamics considers the deconstruction process of complex problems via decomposing all variables, which might influence the problem, into an interrelated network (cf. Sterman 2000: 8–9).

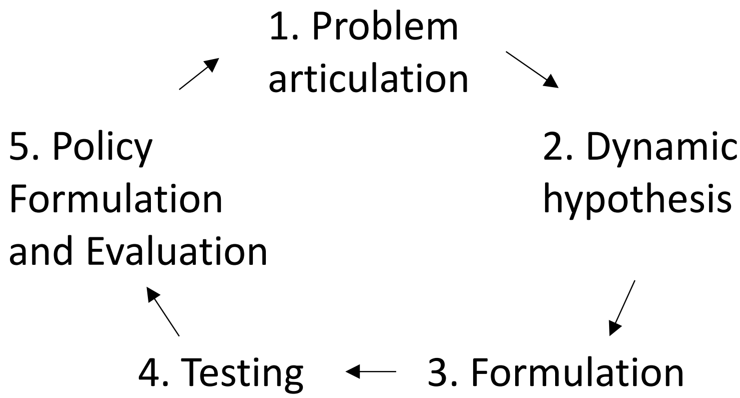


Figure 1: The major Steps in constructing a Model via the System Dynamics Approach
Source: own illustration after Sterman 2000

Explaining the methodology along the individual steps, it can be stated that the first step considers the identification of the real problem along with critical variables and concepts. Furthermore, it is important to characterize the problem dynamically as it is essential for the actual model development. The dynamic hypothesis is derived from the second step by investigating the origin of the problem and building linkages between variables in a causal loop diagram, which will be later transformed into a flow diagram. The third step elucidates the definition of the system dynamics model by translating the flow diagram into the stock, rate and auxiliary equations. Additionally, parameters and behavioral relationships are estimated. The development of the causal loop diagram as well as the flow diagram along with parameter estimations takes place in a computer simulated model through specific software. Regarding the fourth step of the process, the comparison of the simulated behavior of the model and the actual behavior of the system takes place as to validate the model. The fifth and last step considers the interpretation of results as well as evaluating and developing suitable strategies for improvement. (cf. Bala et al. 2017: 17–24)

2.1 Dynamic risk assessment

The dynamic risk assessment process considers the integration of the system dynamics methodology into the classical risk assessment process, which consists of risk identification, risk analysis, and risk evaluation. Referring to the literature review, the components of capacity management have been discussed but solely regarding the airline industry and its passengers. However, in Figure 2 the interrelation of airlines and other participants of the aviation value chain are illustrated to encompass the dynamics of capacity management fully. The figure clarifies the interdependencies of the individual participants regarding supply and demand as well as their direct impact on airline capacity management. Specifically, the impact of original engine manufacturers (OEMs) and airports are highlighted in red within Figure 2. Regarding the effect of OEMs, airlines need to consider long lead times when planning capacity addition through ordering of aircrafts. Furthermore, lead times may extend unexpectedly from time to time. Hence, the relationship of OEMs and airlines needs to be assessed sensitively and respected in particular within flight scheduling (cf. Mack et al. 2013: 16). Concerning the relationship of airlines and airports, airlines have to design the flight schedule in accordance with the airports slot capacity. Moreover, the distribution of flight slots is accounted as highly competitive depending on the airport and the approached route (cf. Barnhart et al. 2012: 143). Therefore, the scope of airline capacity forecasting does not solely relate to internal aspects, but further needs to involve the capacity of other participants of the aviation value chain.

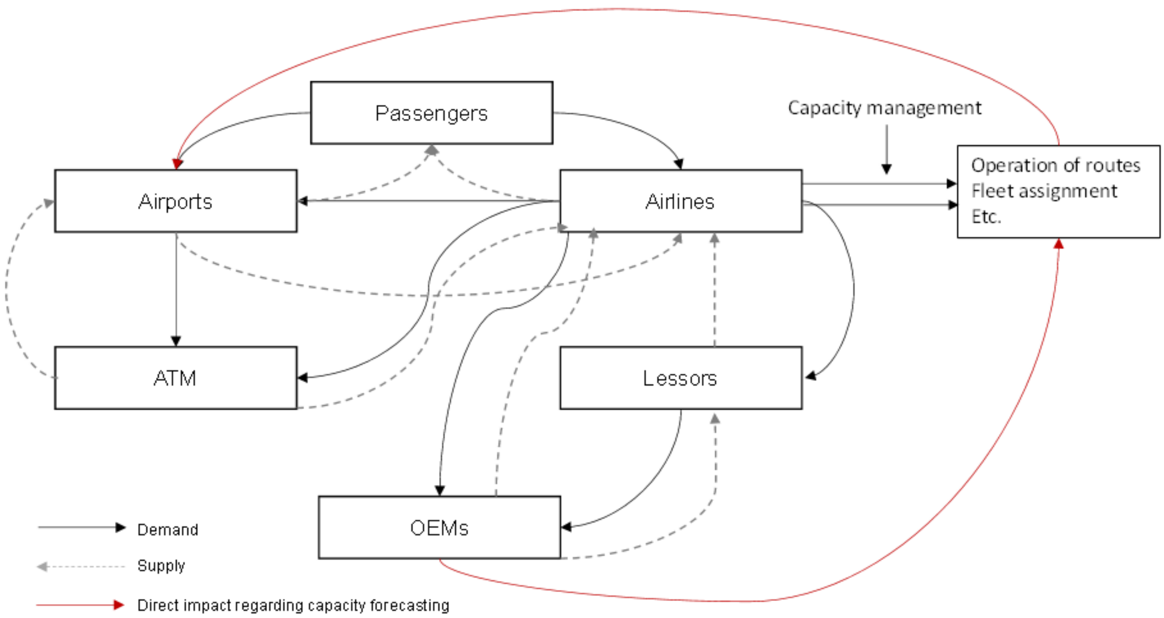


Figure 2: *The Supply-Demand Balance within the Airline Industry*
Source: *own illustration*

In Figure 2 the context of capacity forecasting, which has been elaborated in the theoretical analysis (Part 1) sections of this paper is associated with the risk of fuel price volatility (commodity risk) through further internal business factors regarding costs and revenue. The black lines indicate the relationship of the individual factors, which have been assessed through the literature review. However, the thesis aims to investigate the direct impact of risks on capacity management. The research interest is marked through the dotted line in Figure 3 and encompasses the assessment of the direct impact of commodity risk on capacity forecasting. As risks have not been considered yet in capacity forecasting it would close a gap within the currently existing literature.

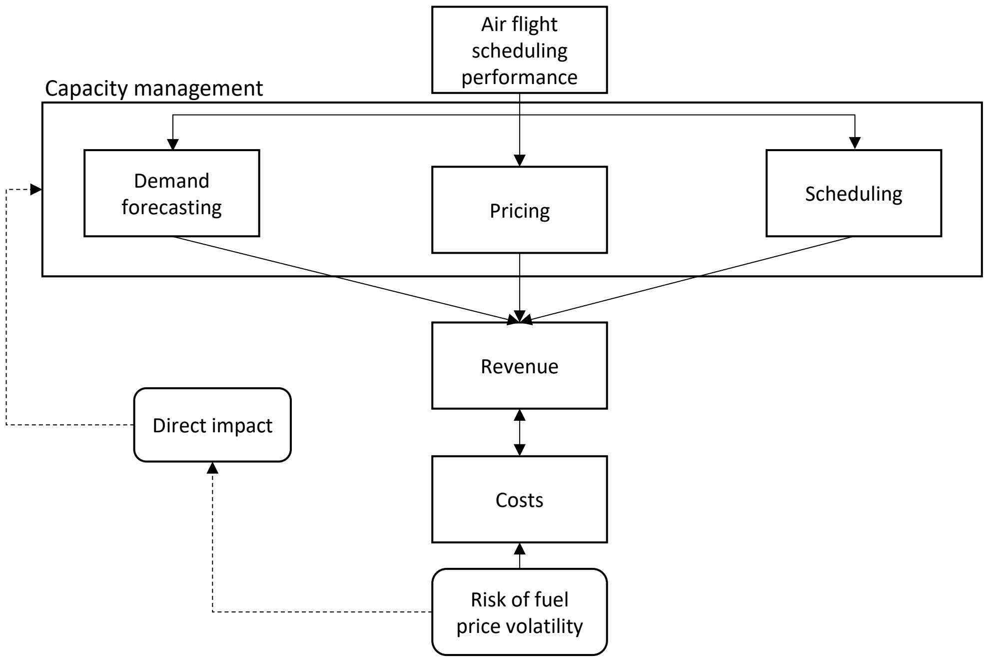


Figure 3: *The direct Impact of Risks on Airline Capacity Management*
Source: *own illustration*

2.2 Risk Identification

As it can be derived from the literature review, specific risks regarding the airline industry have already been identified. However, the thesis focuses solely on the impact of quantitative risks due to measurability. Nevertheless, it is essential to carry out a regular review of the risk identification process.

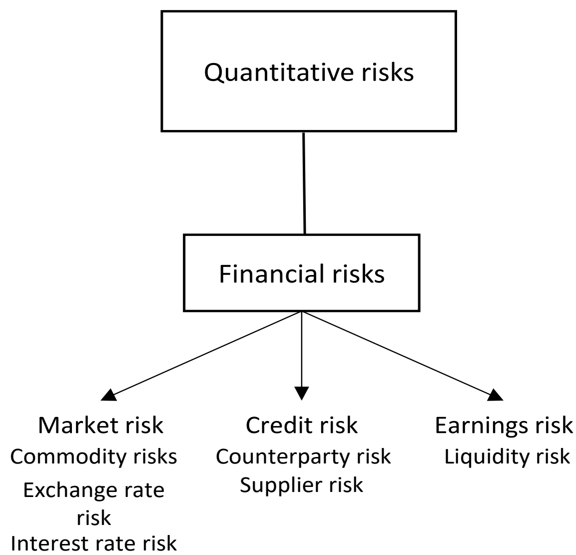


Figure 4: *Quantitative Risks within the Airline Industry*
Source: *own illustration*

The risks indicated in Figure 4 are considered as the most relevant quantitative risks factors to which airlines are exposed. However, this investigation will focus on one risk factor – the risk of fuel price volatility.

Reasoning the choice of risk factor and having a better understanding of the risk factors' background, a reflection of the risk of jet fuel price volatility will follow.

According to the economic performance analysis of the airline industry for the year 2017 of IATA, 18.8% of airlines' annual operating costs amount to fuel cost, which represents a decrease of 1.8% compared to the proportion of airlines' fuel costs in 2016. However, IATA forecasts a further increase in the proportion of fuel costs amounting to 20.5%, as the forecast predicts an increase in fuel usage as well as in fuel prices. The increase in fuel usage is mainly on behalf of the airline itself and driven by various factors regarding among others traffic, the fuel efficiency of aircraft, and inefficiencies of aerospace and airports, which lead to a waste of fuel burn of around 5% each year. (cf. IATA Economics 2017: 4) However, the jet fuel price is influenced differently. Jet fuel is solely a refined product of crude oil, hence, the price for jet fuel follows the price trend of crude oil, as it has been aforementioned. Thus, the drivers of the crude oil price need to be identified. Crude oil is traded on the commodity market, and prices are controlled by traders, who bid on future contracts, which explains the daily fluctuating changes in the crude oil spot price. However, exogenous forces affect the bidding behaviour of the traders.

3 Problem Articulation

Referring to the work of Cronrath (2018), the issue of airline profit cyclicality has been addressed along with possible drivers - capacity management and in particular capacity forecasting. The process of capacity forecasting is of complex nature due to various internal as well as external stimulating factors. These external factors cannot be controlled by the airline and expose it to various risks, which eventually result in a loss.

Dynamic Hypotheses

The influencing dynamics of capacity forecasting have been discussed in the literature review – demand, airfares, and flight-scheduling. Derivating the hypotheses, the capacity forecasting procedure is broken down into a dynamic causal feedback loop system, which emphasizes on the interrelations of the individual internal and external influencing factors. However, due to the scope of this thesis, not all influencing variables are included in the model. Hence there is potential for further investigation concerning expanding the model through involving more relevant factors.

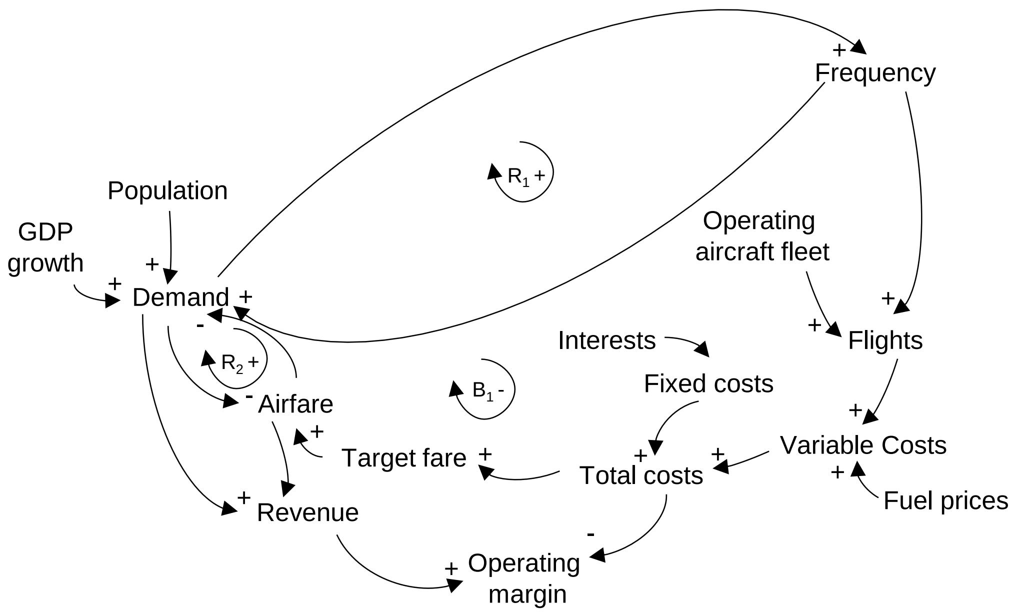


Figure 5: *Simplified Causal Feedback Loop Diagram regarding Airline Capacity Forecasting*
Source: *own illustration*

In Figure 5 a simplified causal feedback loop system regarding airline capacity forecasting is illustrated. It is simplified due to the scope of this thesis. However, the most critical aspects are involved.

The relation between the individual influencing dynamics is marked through arrows. The arrowhead points at the to be stimulated variable, and the polarity of the relation indicates to what extent the variable is stimulated. This relationship is characterized as a cause-effect relationship. A positive polarity indicates that an increase of the output variable leads to an increase of the to be stimulated variable. Regarding the negative polarity of a relation, a decrease in the output variable will lead to a decrease in the to be stimulated variable. Moreover, the interrelation of the influencing dynamics eventually leads to a closed feedback loop. Concerning Bala et al. (2017), a closed feedback loop requires at least two causal-related variables, which close back on themselves. In Figure 5 three closed feedback loops can be identified. Considering the first closed feedback loop, which is marked as R1 + within the loop, it describes the inter-causal relation of demand and frequency of approached routes. As both cause-effect relations show a positive polarity, the closed feedback loop is characterized as reinforcing, which indicates growth. The second closed feedback loop in Figure 5 is labeled as R2+ and incorporates the causal-effect relationships of demand and airfare. Both relationships are assessed with a negative polarity. Nevertheless, the polarity of the whole loop is determined by adding the individual relations. Therefore, in the case of R2+, the closed feedback loop is considered positive as the addition of two negative relations results in a positive loop, and thus, R2+ is considered a reinforcing loop. The third closed feedback loop, which is marked as B1- in Figure 5, considers the causal-effect relationship of the main input factors regarding capacity forecasting:

$$\text{Demand} \xrightarrow{+} \text{Frequency} \xrightarrow{+} \text{Flights} \xrightarrow{+} \text{Variable Costs} \xrightarrow{+} \text{Total Costs} \xrightarrow{+}$$
$$\text{Target Fare} \xrightarrow{+} \text{Airfare} \xrightarrow{-} \text{Demand}$$

Equation 1

Through the addition of the individual polarities, an overall negative polarity is achieved, which results in a balancing feedback loop. A balancing feedback loop aims to maintain the system stability.

There are further causal-effect relations, which stimulate the influencing dynamics. However, these are not considered in the model individually, due to the scope and the focus of this thesis. Nevertheless, these are still involved in the analysis as they are included in the given data set.

As the main closed feedback loops, which describe the most important aspects of capacity forecasting, have been identified, the purpose of the investigation may follow. In the theoretical part (Part 1) the problem of capacity forecasting in the airline industry has been elucidated – complexity and uncertainty. Given the causal feedback loop diagram in Figure 5, it can already be stated that there is a positive causal-effect relationship of fuel prices, variable costs, total costs, and hence, airfare. As fuel price volatility (commodity risk) accounts as to be tested risk factor, the following hypotheses result:

H1a: Commodity risks moderately has a positive effect on costs, hence influencing airfares.

H1b: Commodity risks moderately has a negative effect on costs, hence influencing airfares.

H1c: Strong correlation between risks and airfares have an impact on capacity forecasting.

These hypotheses will be tested via the stock and flow diagram, which will be developed from the causal feedback loop diagram in the next sub-chapter.

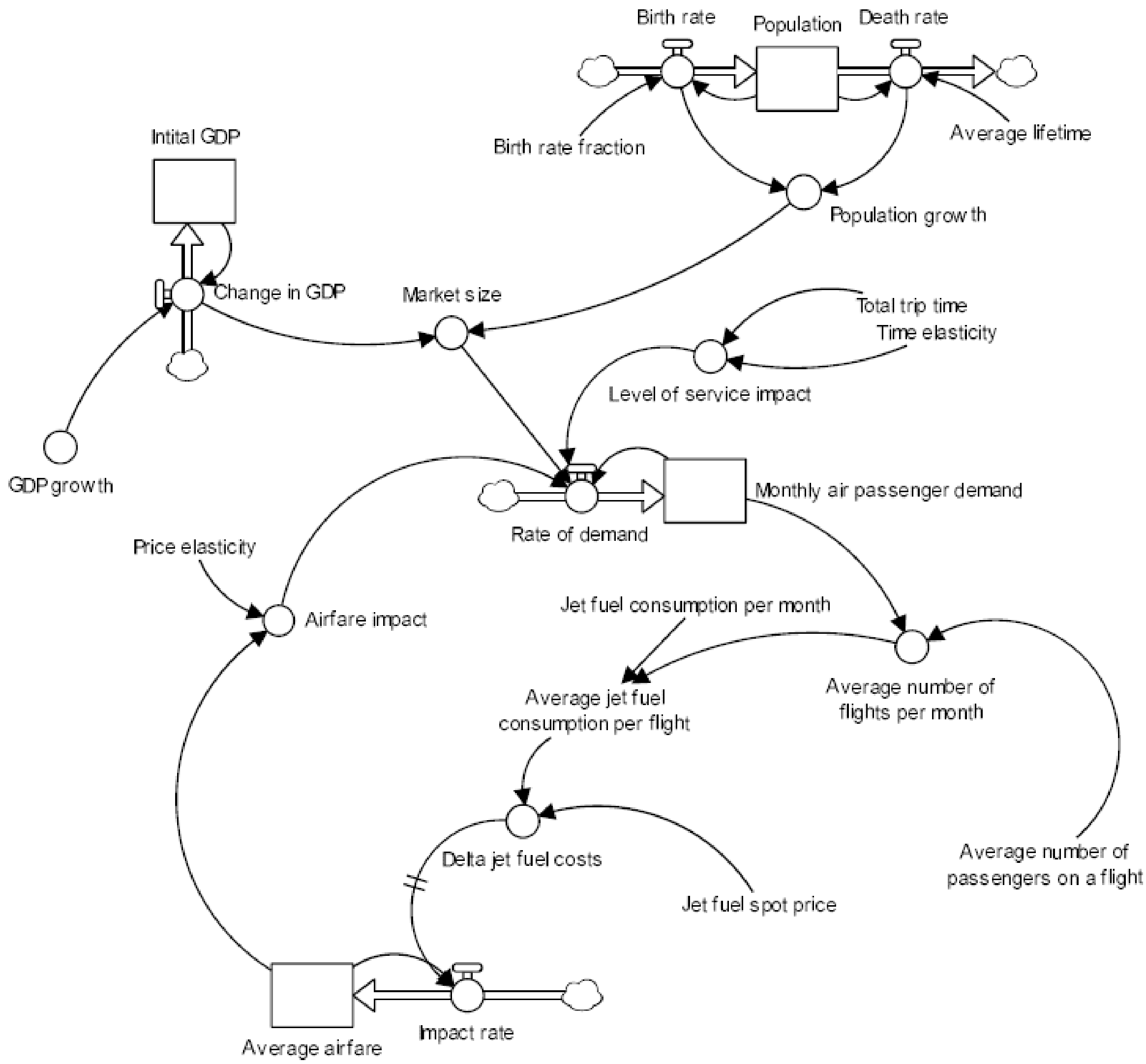


Figure 6: *Stock-Flow Diagram regarding Airline Capacity Forecasting*
Source: *own illustration*

In Figure 5 and Figure 6, a simplified stock-flow diagram regarding airline capacity forecasting is presented. Due to the scope of this paper, not all input variables from Figure 5 can be incorporated into the main model, which is illustrated in Figure 6. Hence, Figure 6 elucidates a further insight into the assessment of air passenger demand. Nevertheless, these are solely descriptively analyzed, while the variables, which are incorporated in the main model, are additionally expressed through mathematical equations.

Regarding the understanding of the model functions, the symbols used in the graphical illustrations, will be explained subsequently. The stock-flow diagram considers three different symbols. The first one is the stock, which is illustrated by a box symbol and its task is to receive input or output from the flow (second symbol) and accumulate and store the numerical value, which has been determined at time t=1 of the model simulation. Since the task of the flow symbol has already been elucidated, it is further to say that it is illustrated by the arrow pointing at the stock symbol. Concerning the last symbol out of the three, which is marked by a circle, it is an auxiliary tool to build additional calculatory procedures within the stock-flow diagram.

The first part of the stock-flow diagram incorporates the demand forecasting through the major input factors concerning the change in GDP, population growth, level of service impact, and airfare impact.

The stock GDP is affected by the change in GDP implying a multiplication of the initial GDP value with the GDP growth fraction. The initial GDP value may be provided through a data set at time t1 within the model and accumulates over time through the input of the flow change in GDP.

Moving on to the determination of the growth in population, the stock of population is affected by the inflow through births and the outflow through deaths. Here, the birth rate is assessed through the fractional birth rate, while the death rate depends on the average lifetime. Hence, the growth in population is determined by the difference of births and deaths within a population. The multiplication of the population growth and the growth in GDP specify the market size for the air passenger demand.

A further influencing variable is the impact of service level, which measures consumers time sensitivity through the average total trip time and the consumer’s time elasticity. The total trip time involves elements beyond the actual flight time and considers among others the time consumed for check-in, boarding, waiting time due to connecting flights, and additional waiting time in case of delay. These elements may vary in their length and affect consumer behavior, which is assessed by time elasticity. Barnhart et al. (2009) describe time elasticity as a factor, which depends on the type of consumer. Business travelers seem to be more elastic concerning time than price-conscious travelers who show a rather inelastic behavior. Furthermore, the rate of demand is affected by the airfare impact incorporating the change in airfare, which will be described more in detail further below.

Together, the market size, the service level impact, and the airfare impact determine the rate of demand, which provides input flow for the air passenger demand.

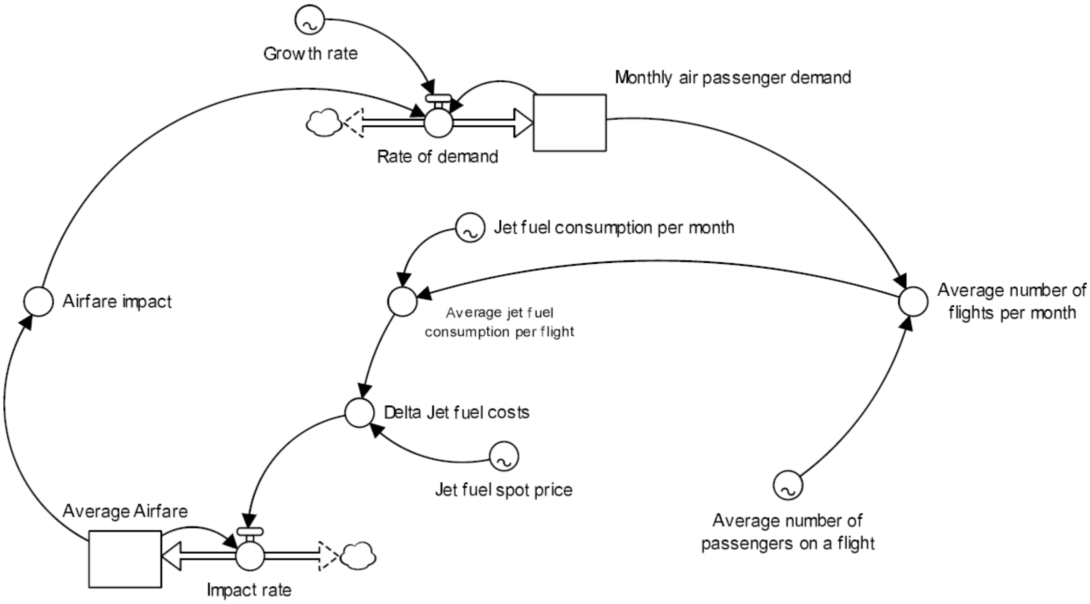


Figure 7: Relevant Stock-Flow Diagram regarding Airline Capacity Forecasting
Source: own illustration

As aforementioned, the stock flow diagram in Figure 7 incorporates a less extensive approach regarding demand forecasting. Thus, the input variables concerning market size and impact of service level are expressed through the variable growth rate, which influences the rate of demand along with the airfare impact. The rate of demand functions as a flow providing the input for the stock monthly air passenger demand (D) throughout the time horizon of the model run. It is assessed through the following mathematical equation.

$$\text{Rate of demand}_t = D_{t-1} + (\text{Growth rate}_t + \text{Airfare impact}_t) * D_t$$

Equation 2

The variables, which imply a mathematical assessment, are re-calculated for every time the model runs. For variables, which incorporate a given data set, the specific value for time t is derived from a graphical function, which has been built before running the model by inserting the respective data. In equation 2, the growth rate incorporates a given set of values regarding the monthly average growth rate of air passenger demand, while the airfare impact receives its input parameters from the stock average airfare. Furthermore, it involves the change of airfare at time t.

$$\text{Airfare impact}_t = \text{Airfare}_t - \text{Airfare}_{t-1}$$

Equation 3

The average airfare is expressed as stock in the model and receives for time t1 an input value from the data set. Further average airfare values are calculated through the flow impact rate. The impact rate implies a percentage of the change in jet fuel costs, which are directly passed on to the airfare and hence, the passenger. In this thesis, only the change in jet fuel costs is considered to be passed on to the passenger as it is assumed that other cost elements are not exposed to comparable volatility. In the literature, various passing through rates have been discussed, varying from 0% to 100%. However, it strongly depends on the competitive mode of the industry and within the airline business even on the competition on specific routes. If there was perfect competition, 100% of the costs could be passed on to the passenger. Nevertheless, most of the time an oligopolistic scenario is applicable, which considers a pass-through rate of about 0-50%. Yet, most studies rather assume the existence of a pass-through rate, hence the empirical evidence for the pass-through of costs depends on the individual investigation (cf. Koopmans/Lieshout 2016: 4–8).

The change in costs, which are part of the impact rate incorporates the jet fuel spot price per gallon (P) and the average jet fuel consumption per flight, as well as the average number of seats within an aircraft. In Figure 6, the connecting arrow between Delta jet fuel costs and the passing through rate implies two horizontal lines, which indicate a delay of impact. It is necessary to consider a delay within the model, as a rise in costs cannot be passed on immediately because an increase in costs might occur in a later point in time than the actual determination of the airfare. The mathematical assessment of the change in jet fuel costs (△ Jet fuel costs) is described by the following formula:

$$\Delta\, Jet\ fuel\ costs\ per\ seat = \frac{(\,P_t - P_{t-1}) * Average\ jet\ fuel\ consumption\ per\ flight}{Average\ number\ of\ seats}$$

Equation 4

The average jet fuel consumption is assessed in the following matter, whereas the average jet fuel consumption per month is provided through the data set:

$$Average\ jet\ fuel\ consumption\ per\ flight = \frac{Average\ jet\ fuel\ consumption\ per\ month}{Average\ number\ of\ flights\ per\ month}$$

Equation 5

It has been mentioned that the average airfare is affected by the flow impact rate at time t, which reflects the proportion of the average airfare at time t along with the change in jet fuel at time t-x and the pass-through rate in percent. Due to the impact of delay, the change in jet fuel costs is assessed at time t-x. However, the exact period of delay will be estimated in the further development of the thesis. Furthermore, the calculation procedure of the impact rate can be derived from the following mathematical equation:

$$Impact\ rate_t = Average\ airfare_t * \Delta Jet\ fuel\ costs\ per\ seat_{t-x} * Pass\ through\ rate\ \%$$

Equation 6

The variable implying the average number of flights per month is determined through the relation of the annual air passenger demand and the average number of passengers on a flight, which is derived from the data set, in the following matter:

$$Average\ number\ of\ flights\ per\ month = \frac{Monthly\ air\ passenger\ demand}{(Average\ number\ of\ passengers\ in\ a\ flight)}$$

Equation 7

This makes up the total stock-flow diagram and describes a simplified approach to capacity forecasting. In the next step, the input variables for the model are provided and will be tested with a particular focus on the impact of the jet fuel price volatility on the entire system.

4 Testing

The testing involves the quantification of the model, which has been formulated in the previous subchapter. Beforehand, the main input variables regarding the relation of the monthly average jet fuel spot price per gallon (jet fuel spot price p.g. (M)) and the costs of jet fuel per gallon (jet fuel costs p.g.) as well as the quarterly average jet fuel spot price per gallon (jet fuel spot price p.g. (Q)) and the average airfare will be tested concerning their statistical relevance through a correlation analysis. The elucidation of the procedure may be introduced in the subsequent paragraph.

Measuring the strength of the relationship between two variables, the covariance, the coefficient of correlation, and the coefficient of determination will be used for the assessment. According to Keller (2012), the statistical measurements build upon one another. Thus, all of them will be calculated successively, though the covariance is not perceived a reliable tool of analysis as it solely provides information about whether the relationship between a dependent and an independent variable is positive or negative. The formula for assessing the covariance of a sample of data is provided in equation 8.

$$S_{xy} = \frac{\sum_{i=1}^{N}(x_i - \overline{x}) * (y_i - \overline{y})}{n-1}$$

Equation 8

The covariance for a data sample describes mathematically, the differences between each independent variable x and each dependent variable y and their mean within the data set. For a detailed description of the variables see Appendix. Furthermore, it is divided by the total number of data inputs less 1.

Moving on to the coefficient of correlation, which conversely measures the strength of the relationship between the two variables by dividing the covariance through the variable's standard deviation. It is described mathematically in equation 9 along with the mathematical derivation of the standard deviation in equation 10.

$$r = \frac{S_{xy}}{S_x S_y}$$

Equation 9

$$s_x = \sqrt{s^2{}_x}$$

Equation 10

The procedure above is also known as the Pearson’s correlation coefficient and provides an evaluation of the relationship through upper and lower limits. Considering the coefficient of correlation as the variable r, the limits are determined in the following way in equation 11:

$$-1 \leq r \leq 1$$

Equation 11

As the relationship can be either of positive or negative nature, the limit is set between -1 and 1. However, a strong relationship is assessed if it is close to the value 1, while a weak relationship is close to the value 0. As the gap between the upper and lower limits is still enormous, the coefficient of correlation is not considered precise. Thus, the coefficient of determination is calculated to obtain the explained and unexplained proportions of the relationship, which implies to what extent the variation of the dependent variable is explained through the variation in the independent variable. This is measured by squaring the coefficient of correlation r. Furthermore, the mathematical equations for the coefficient of determination for a data sample can be obtained from equation 12.

$$R^2 = r^2$$

Equation 12

However, the correlation of values is not an indicator of causation, as this might be influenced by other variables.

As the theoretical approach to the assessment of the relationship between two variables has been provided, the correlation analysis will be performed on the main input variables of the model. Due to a clear illustration, the dependent variables and the independent variable are presented along with numerical measurements in Table 1. The data refers to the domestic US airline market involving major, national, and regional carriers concerning scheduled flights only in the time frame of 2003 and 2016 and is derived from the Bureau of Transportation Statistics (2018a). Furthermore, the primary input variables involve the values of the jet fuel spot price p.g. (M) and the jet fuel costs, the values of the jet fuel spot price per gallon (p.g.) (Q) and the quarterly average values of the average airfare.

The impact of delay has been mentioned in the theoretical section of Part 1 and will be included as well in the correlation analysis. The delay d is expressed in months and considers a shift of the jet fuel spot price along with the timeline. Hence, the shift obtains, for instance, the coefficient of correlation of the average airfare at time t and the jet fuel spot price p.g. (Q) at time t-3. Furthermore, a delay is considered not only concerning the average airfare but also the jet fuel costs.

Table 1: The Correlation of the independent Variable Jet Fuel Spot Price p.g. and the dependent Variables Jet Fuel Costs and average Airfare

	Sample standard deviation	Sample covariance	Sample coefficient of correlation	Coefficient of determination
Jet fuel spot price p.g.(M) d=0	0,784797674			
Jet fuel spot price p.g. (Q) d=0	0,777465358			
Jet fuel costs d=0	**0,76770914**	**0,5847151**	**0,97048739**	**0,94184579**
Average airfare d=0	28,99645346	13,216396	0,5862558	0,34369578
Jet fuel spot price p.g. (M) d=3	0,799174			
Jet fuel spot price p.g. (Q) d=3	0,791104142			
Jet fuel costs d=3	0,76770914	0,575504637	0,93801713	0,879876136
Average airfare d=3	28,99645346	15,39925295	0,671306901	0,450652955
Jet fuel spot price p.g. (M) d=6	0,811981982			
Jet fuel spot price p.g. (Q) d=6	0,804338405			
Jet fuel costs d=6	0,76770914	0,521698348	0,836905375	0,700410607
Average airfare d=6	**28,99645346**	**16,05882491**	**0,688541426**	**0,474089296**
Jet fuel spot price p.g. (M) d=9	0,82620344			
Jet fuel spot price p.g. (Q) d=9	0,816916666			
Jet fuel costs d=9	0,76770914	0,474804289	0,748567422	0,560353186
Average airfare d=9	28,99645346	15,96518357	0,673986624	0,454257969

Source: own table

According to the results in Table 1 the jet fuel price p.g. (M) and the jet fuel costs p.g. at d=0 show the most substantial relationship in which 94% of the variation in jet fuel costs p.g. can be explained through the variation in the jet fuel spot price p.g. (M). The scatterplot in Figure 8 provides visual support of the result. Therefore, it can be derived that the jet fuel costs p.g. are partially following the movements of the jet fuel spot price p.g. (M), as it shows to a certain extent the same volatile pattern. Hence, the first part of the hypothesis1a is true, and the hypothesis1b is rejected.

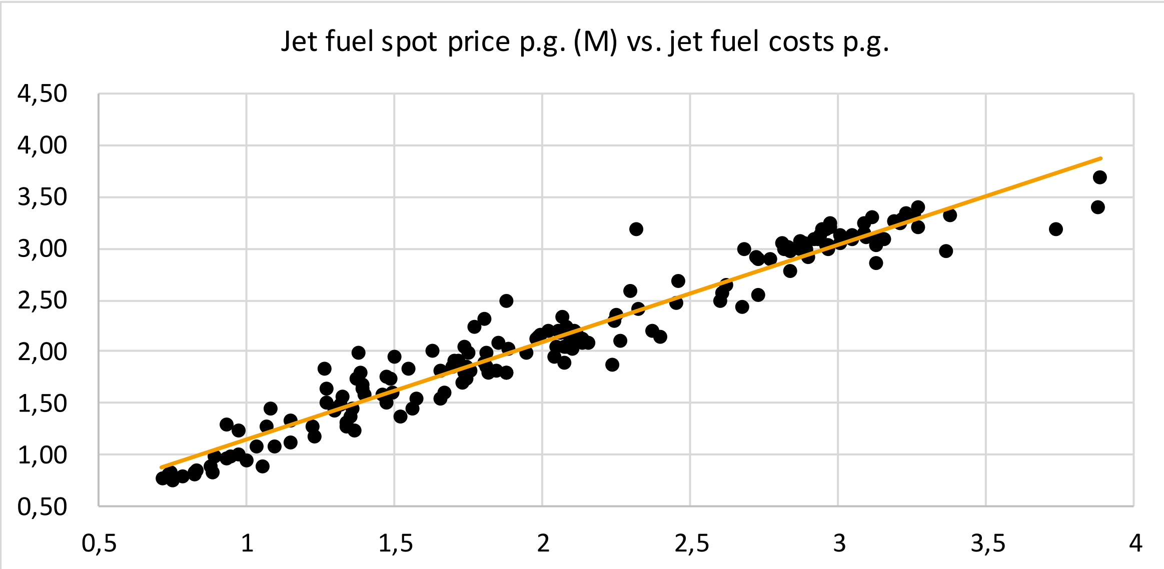


Figure 8: *Scatterplot of Jet fuel price p.g. (M) vs. Jet fuel costs p.g. at d=0*
Source: *own illustration*

Concerning the correlation analysis of the jet fuel spot price p.g. (Q) and the average airfare, the most robust relation has been assessed at d=6, which considers a 6-month delay of the impact of the jet fuel spot price at time t on the average airfare. Nevertheless, this relationship is not assessed strong due to the enormous number of outliers and their distance from the regression line, which can be observed in the scatterplot in Figure 9. However, to entirely reject the hypotheses H1a and H2, the impact of the change in jet fuel spot price on the average airfare will be further assessed by the primary model - the stock-flow diagram.

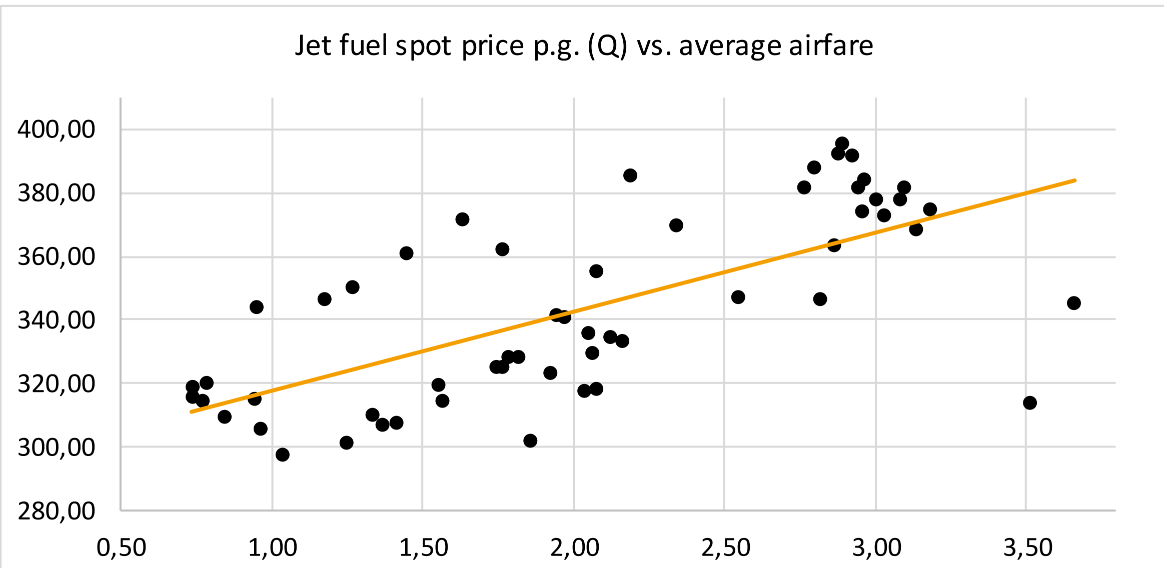


Figure 9: *Scatterplot of the Jet Fuel Spot Price p.g. (Q) and the Average airfare at d=6*
Source: *own illustration*

Moving on to the testing of the impact of the change in jet fuel spot price on the average airfare and hence, capacity forecasting, the necessary starting variables for the model run, are presented in Table 2.

Furthermore, the delay of the impact of the change in jet fuel spot price p.g. on the average airfare needs to be distinguished. Due to the results of the correlation analysis, a delayed impact of 9 months will be included in the model simulation. Due to the data set, which provides for monthly data starting from 2003 to 2016, the model will run in total through 168 months.

Table 2: Starting Variables for the Testing Procedure of the Stock-Flow Diagram

Variable	Value
Average airfare at t=1 (in US-$)	315,77
Monthly air passenger demand at t=1 (people)	49.757.124,00
Average number of seats on a plane	180
Pass-through rate (in %)	5

Source: own table

As it has been mentioned before, the variables regarding the jet fuel spot price, the growth rate, the monthly average fuel consumption, and the average number of passengers on a flight are wholly derived from the dataset, which can be obtained from the Appendix 2. Thus, solely an evaluation of the variables, which have been calculated by the model itself, may take place and are presented in the subsequent Figures 10 to 18.

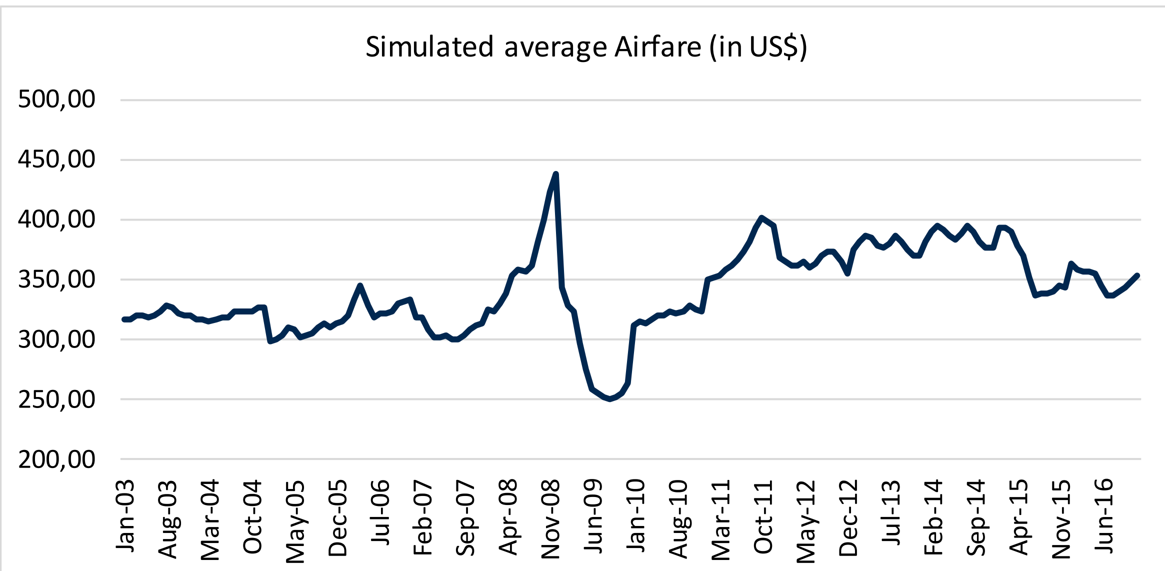


Figure 10: Simulated average Airfare (in US$)
Source: own illustration

In Figure 10, the simulated average airfare is presented, which directly reflects the received input from the simulated impact rate illustrated in Figure 11. The simulated average airfare maintains relatively stable between January 2003 and October 2004, after that the first major price decrease of about $20 is achieved. However, between October 2004 and December 2006 increased volatility in the average airfare is perceived, which further incorporates an overall price increase with a price peak in April 2006. On the part of the simulated impact rate, it increases to nearly 20$ per flight ticket in April 2006 and it is reduced by almost $30 within May 2006. This becomes visible through the enormous up and down swings within the graph. The augmentation is followed by a reduction until August 2007, after that the average airfare expands enormously to its maximum value of about $438 in December 2008. However, this enormous rise is pursued by a massive abatement, which reaches its lowest level of $251 in September 2009. On the part of the impact rate, during the period of August 2007 and December 2008 a steady growth of the impact of change in jet fuel spot price can be perceived. Nevertheless, the impact rate diminishes after December 2008 and extreme jumps can be observed, which involve a maximum negative impact rate of nearly $ -37 in the month of April 2009. In the period of September 2009 to November 2011, the simulated average airfare recovers from the immense downturn and augments steadily, while reaching another peak of nearly $400 in November 2011. The simulated impact rate influences the growth of the simulated average airfare by mostly positive rates and less extreme rate volatility. The price volatility of the simulated average airfare remains between $350 and $400 until April 2015. After that, the price decreases again to $335 in July 2015 is then exposed to relatively small price swings, as it can be observed through the simulated impact rate.

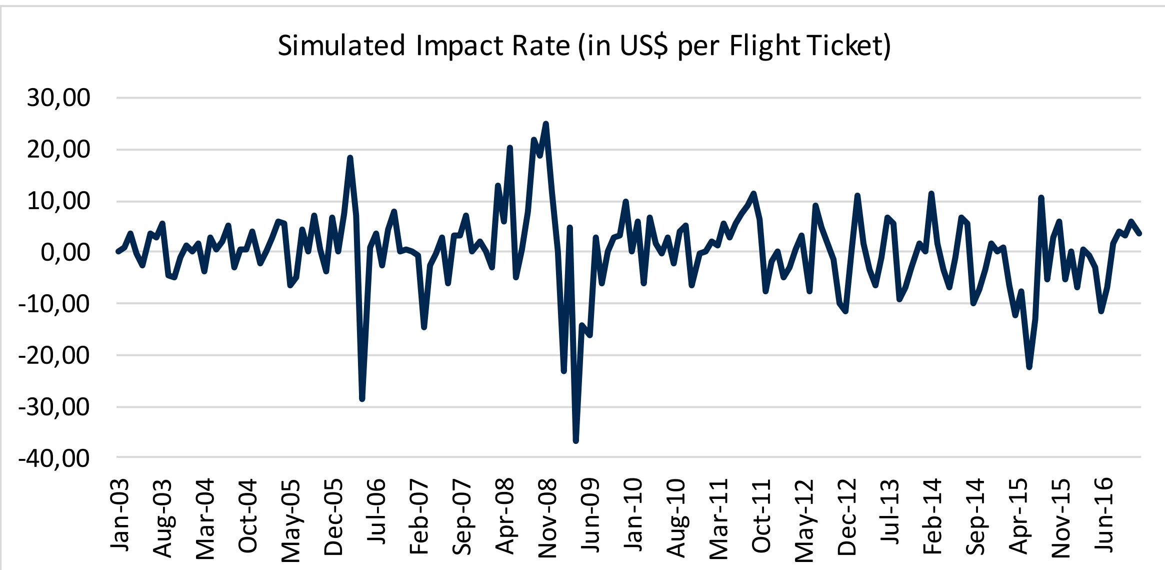


Figure 11: Simulated Impact Rate (in US$ per Flight Ticket)
Source: own illustration

Furthermore, the simulated average airfare influences the airfare impact and hence, the rate in demand as well as the monthly air passenger demand. The illustrations for the airfare impact, the rate in demand, and the monthly air passenger demand are provided accordingly in Figure 12 to 14. The similarity in the pattern of the simulated airfare impact and the simulated impact rate is enormous. However, this is explained through the calculation of the simulated airfare impact, as it solely considers the change in the simulated average airfare.

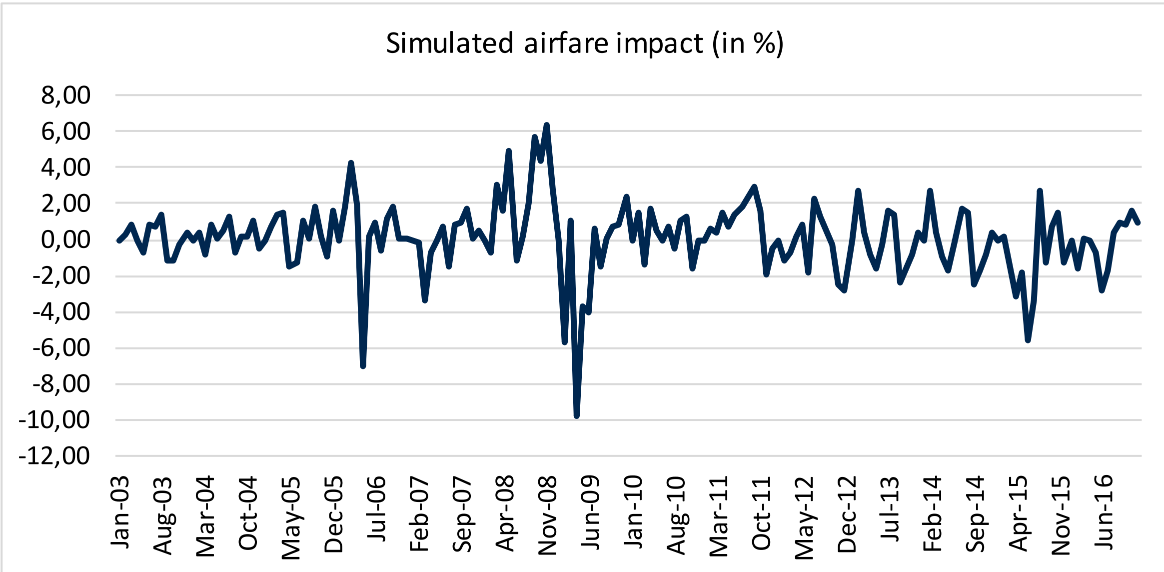


Figure 12: Simulated Airfare Impact (in %)
Source: own illustration

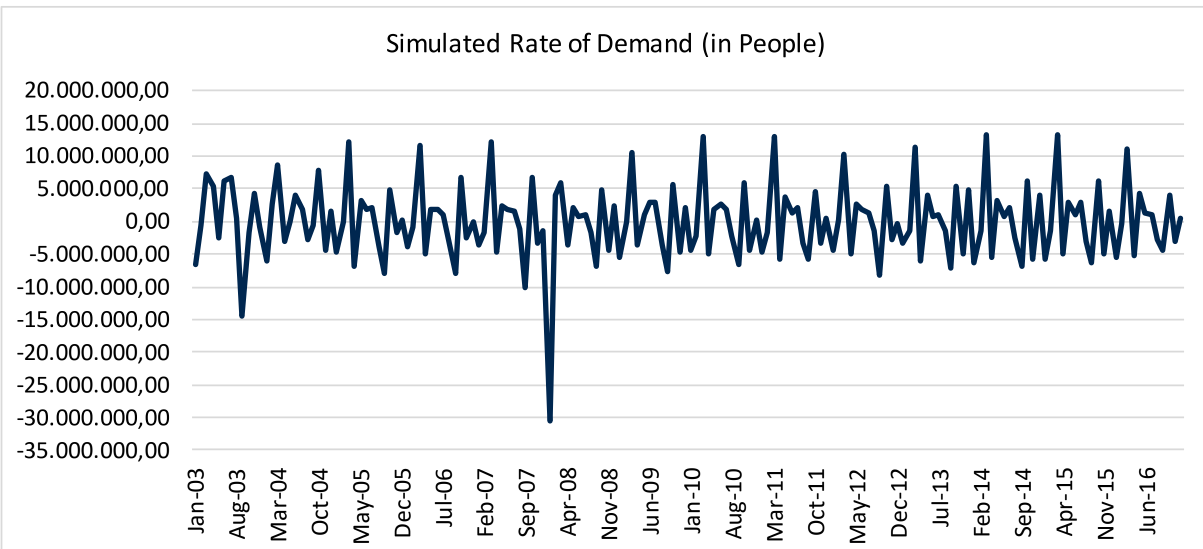


Figure 13: Simulated Rate of Demand (in People)
Source: own illustration

The simulated rate of demand passes through a cyclical development of up and downturns throughout the entire time horizon of the model run. On the average, it incorporates swings of +/- 10.000.000 air passengers per month. However, in September 2003, and especially in January 2008, enormous deviations of the pattern can be observed. Nevertheless, it cannot be explained through the simulated airfare impact as it accounts for nearly 0 in January 2008. Since the simulated monthly air passenger demand is directly affected by the simulated rate of demand, it shows the same behavioral pattern, which is also considered relevant for the simulated average number of flights per month illustrated in Figure 15, as it is to one part calculated from the simulated monthly air passenger demand.

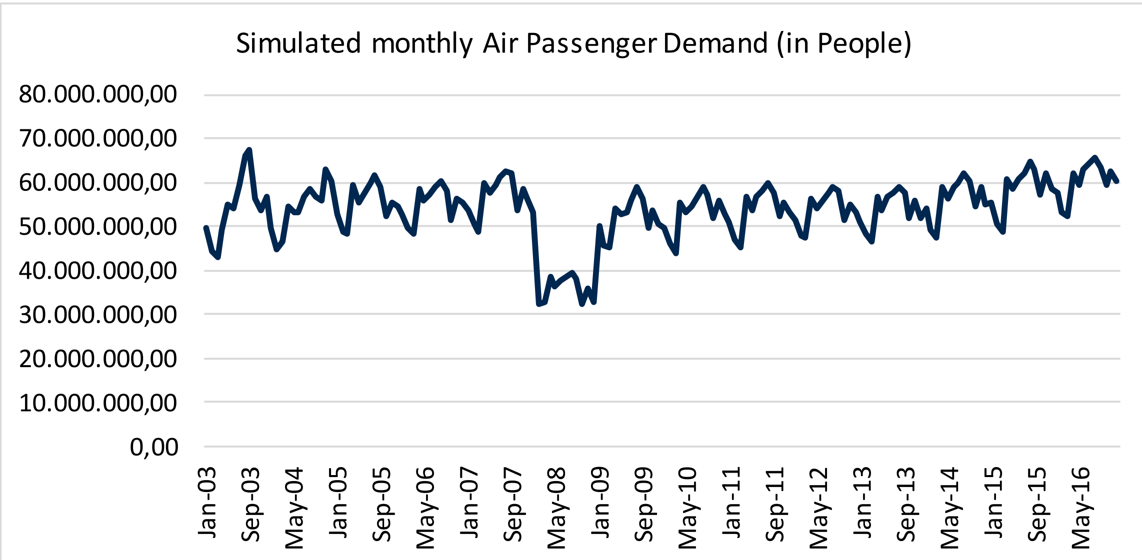


Figure 14: *Simulated monthly Air Passenger Demand (in People)*
Source: *own illustration*

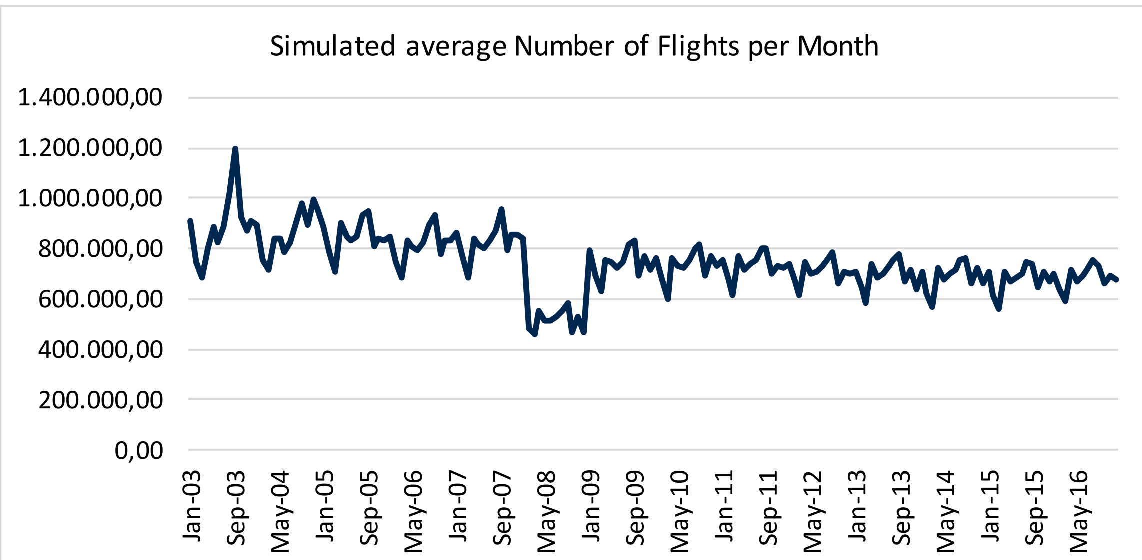


Figure 15: *Simulated average Number of Flights per Month*
Source: *own illustration*

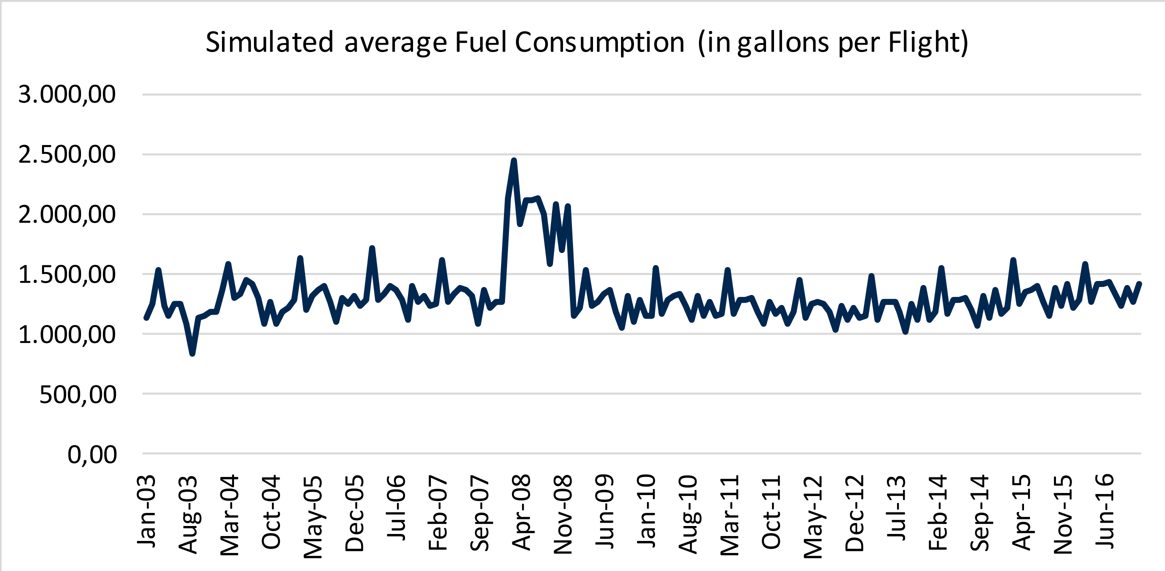


Figure 16: *Simulated average Fuel Consumption (in gallons per Flight)*
Source: *own illustration*

In Figure 16, the simulated average fuel consumption per flight is presented. Overall, a reflection of the simulated average number of flights per month is noticed, which is due to the calculation procedure and is in particular recognized in the year of 2009. Hence, a decrease of the simulated average number of flights per month increases the simulated average fuel consumption per flight.

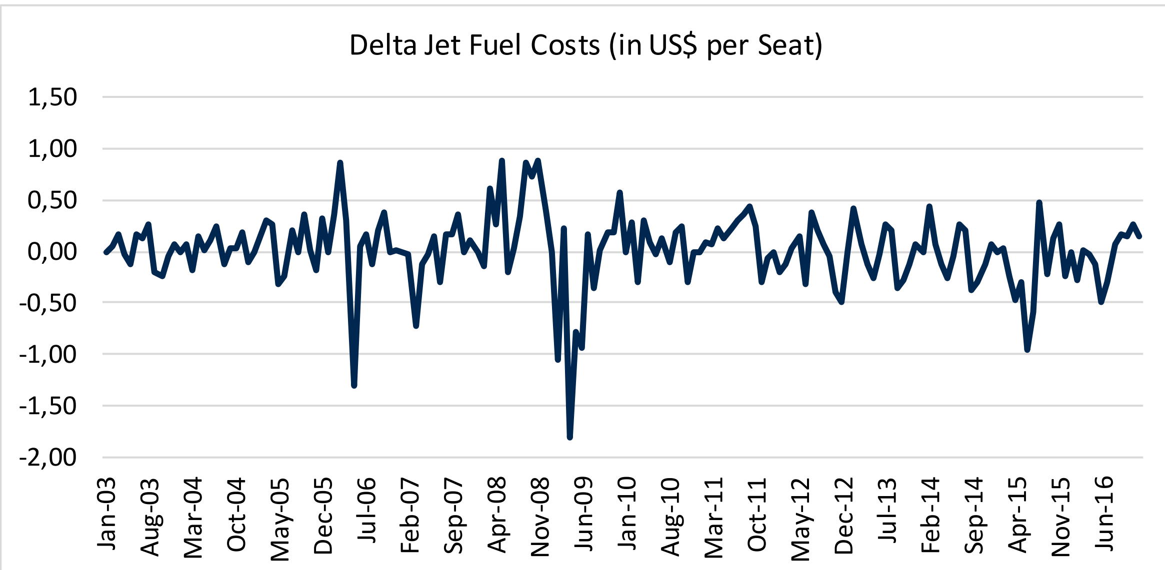


Figure 17: *Delta Jet Fuel Costs (in US$ per Seat)*
Source: *own illustration*

Furthermore, in Figure 17 the change in jet fuel costs is illustrated, which is accounted as one of the major input factors within the stock-flow diagram, due to its direct effect on the impact rate. The change in jet fuel costs is strongly affected by the change in the jet fuel spot price, hence its behavioral pattern is relatable to the one of the jet fuel spot price, which is illustrated in Figure 18. However, the impact of delay of 6 months is to be considered comparing the behavioral pattern of the variables. Hence, the enormous price decrease from July 2008 on, regarding the jet fuel spot price, is observed 6 months later in the change in jet fuel costs.

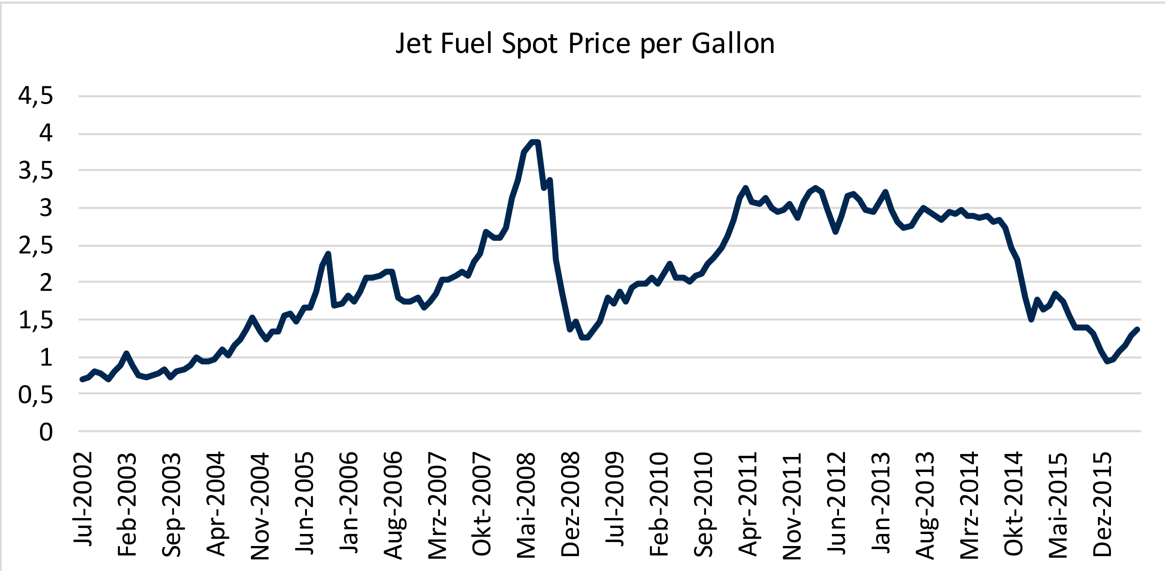


Figure 18: Jet Fuel Spot Price per Gallon
Source: own illustration based on U.S. Energy Information Administration 2018

Resuming the descriptive analysis of the simulation results, the system structure of the stock-flow diagram becomes visible due to the interdependency of the variables within the system. Hence, the evaluation procedure through validation may finalize the testing process.

The evaluation of the model results starts with the validation process of the model's system structure, as validity implies the confidence in a model's usefulness (cf. Forrester/Senge 1978: 8). Due to the nature of system dynamics, the validation procedure starts with the qualitative verification of the model structure. According to Forrester/Senge (1978), the first steps within the verification process aims to compare the relationships within the built model to real existing relationships within the system. These are obtained from the model builder's expertise and are further supported by the literature. Furthermore, a parameter analysis is conducted by collating the quantitive data, derived from the model to an actual dataset. Quantitative empirical evidence for validation is achieved if the error-rate is assessed below 0.05 (cf. Barlas 1996: 207). Correspondingly, the estimation procedure of the error rate is elucidated in the following equations.

$$Error\ rate = \frac{|\bar{S} - \bar{A}|}{\bar{A}}$$

Equation 13

The variable S indicates the values from the model simulation, while the variable A presents the values from the corresponding dataset. Accordingly, the mean for each set of variables is calculated. This is expressed through equation 14 and 15.

$$\overline{S} = \frac{1}{n}\sum_{i=1}^{n} S_i$$

Equation 14

$$\overline{A} = \frac{1}{n}\sum_{i=1}^{n} A_i$$

Equation 15

Nevertheless, the paper proceeds with the qualitative verification process of the model structure. Referring to the sub-chapter in the literature review, the components of capacity forecasting have been elucidated – demand, pricing, and flight scheduling. The stock-flow diagram involves all three of them, even though the component regarding flight scheduling is solely approached via the number of flights per months as well as the average number of passengers on a flight but this is due to the area of investigation – the complete US airline market.

Concerning the interdependencies of the model variables, some can be verified because of its logic nature and others with further references from the literature. Regarding the average jet fuel consumption per flight, the relationship between fuel consumption and a number of flights is of logic nature, as an increase in the number of flights leads to an increase in fuel consumption. Certainly, technical characteristics regarding the type of aircraft, fuel efficiency, and distance of flights need to be involved in the concrete planning procedure. Nevertheless, this is not applicable to the model of this thesis, as the model is tested for the industry and not a specific airline. Furthermore, the costs of jet fuel are bound to the jet fuel spot price, even though airlines make use of long-term contracts with fuel suppliers and of hedging. Nevertheless, airlines tend to hedge solely one to two-thirds of their planned fuel consumption with a time horizon of 6 months into the future (cf. Morrell/Swan 2006: 713). Therefore, airlines are obliged to buy a large amount of jet fuel directly on the spot market. Moving on to the impact of the change in jet fuel costs on the airfare, the notion of pass-through rates has been already mentioned above, even though there is no concrete empirical proof for pass-through rates, as it strongly depends on the competition of the individual route markets (cf. Koopmans/Lieshout 2016: 4–8). Therefore, a rather small rate of solely 5% is assumed. Regarding the impact of the change in airfare on the air passenger demand, the component of the price sensitivity of air passengers needs to be considered, which is expressed through the consumer's price elasticity. According to Morrell (2009), some capacity forecasting approaches consider the aspect of consumer price elasticity and Belobaba/Simpson (1992) involve it in their O-D demand assessment model.

Resuming the prior paragraph, the model structure is perceived verified as the components of the structure, and their interdependencies are covered by the nature of logic as well as literature. Hence, the quantitative evaluation may succeed.

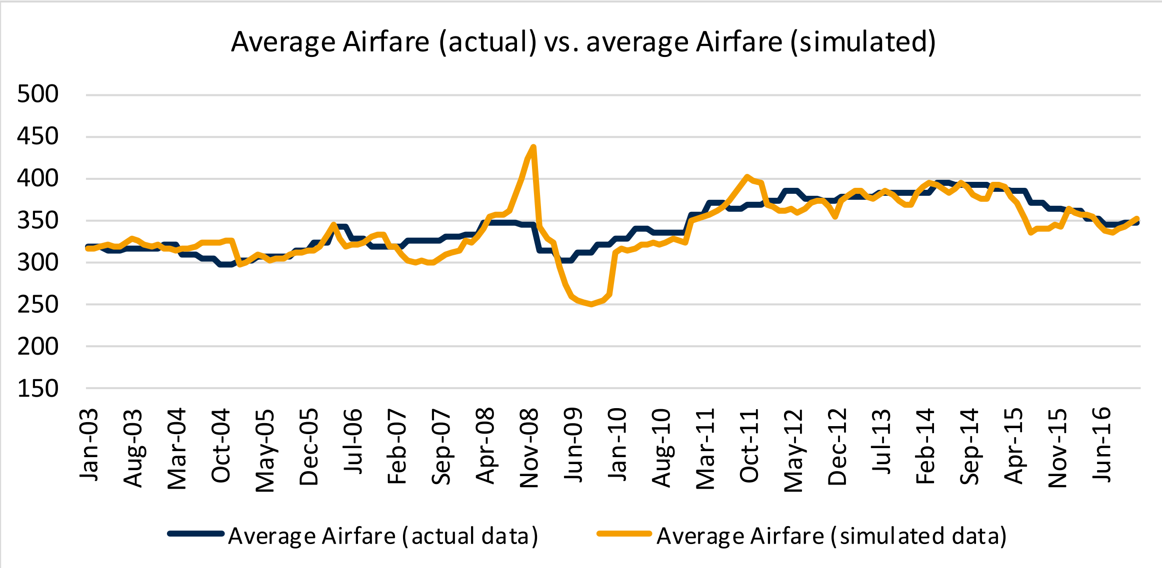


Figure 19: *Average Airfare (actual) vs. average Airfare (simulated)*
Source: *own illustration*

In Figure 19, the comparison of the actual average airfare values and the simulated average airfare values is illustrated. The variables do not move in the exact same pattern; however, they move most of the time within the same range of values, except for the years 2008 and 2009. There, the simulated average airfare exceeds the actual average airfare to a significant extent in 2008. On the part of the year 2009, the simulated variable's values are way below the actual variable's ones.

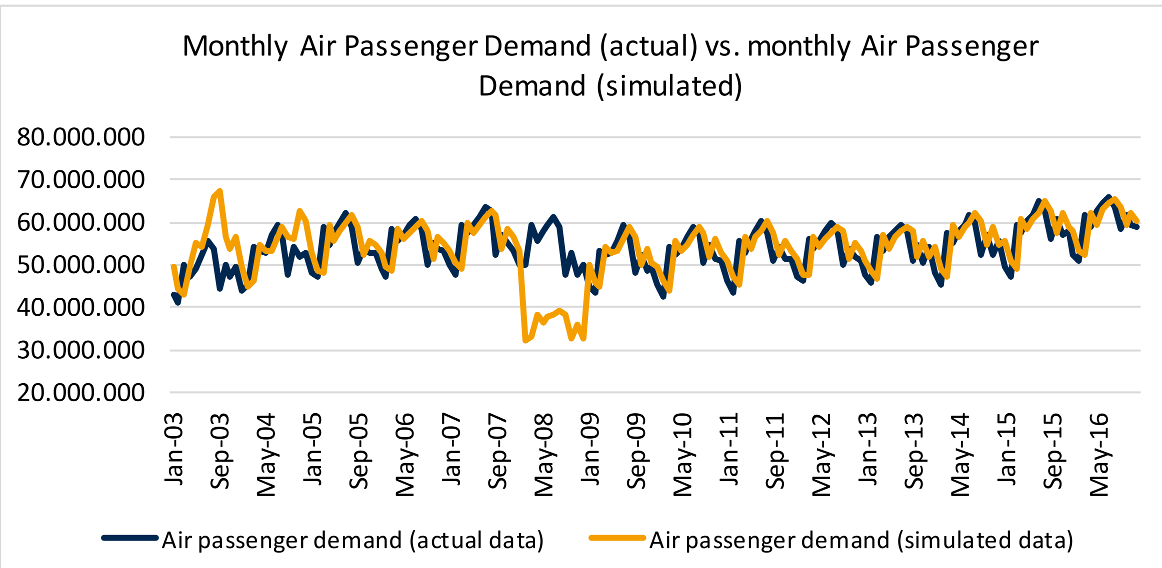


Figure 20: *Air Passenger Demand (actual) vs. Air Passenger Demand (simulated)*
Source: *own illustration*

Furthermore, the comparison of the actual monthly air passenger demand and the simulated monthly air passenger demand, which is graphically presented in Figure 20 visualizes that the behavioral pattern of the variables is closely related but for two periods. The model estimated a significantly higher demand at the beginning of the simulation. For September 2003, the model calculated demand of nearly 67 million monthly air passengers, while the actual monthly demand for September 2003 solely conducts about 44 million air passengers. Moreover, in the year of 2008, the simulation assessed the demand for the entire year way below the actual one.

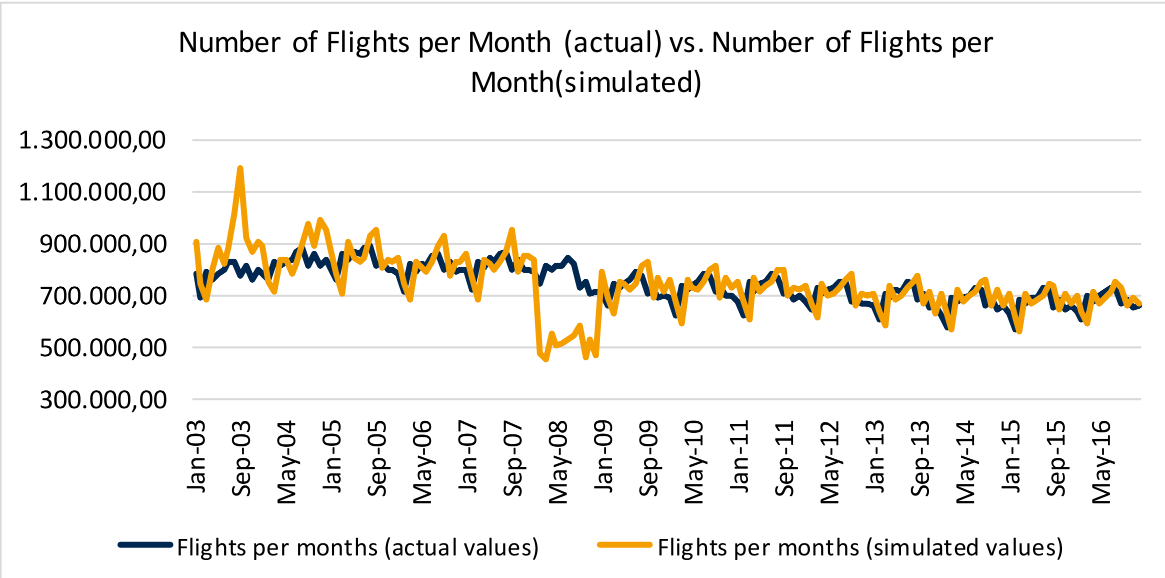


Figure 21: Number of Flights per Month (actual) vs. Number of Flights per Month (simulated)
Source: own illustration

As it has been already observable during the descriptive analysis of the individual simulation results, the number of flights per month move in the same behavior pattern as the monthly air passenger demand. Comparing the actual number of flights per month to the ones from the model simulation, the following can be obtained through the graphical presentation in Figure 21. Again, at the beginning of the simulation process during 2003, the simulated number of flights per month is assessed way above the actual number of flights per month. Moreover, in the year 2008, the stock-flow diagram estimated the number of flights per month way below the actual values.

Moving on to the quantitative evaluation procedure involving the approach of the error rate, the following results have been calculated for the monthly average airfare, the monthly air passenger demand and the monthly number of flights. These are provided in Table 3.

Table 3: Quantitative Comparison of actual and simulated Values

Variable	**Actual value ($\overline{A}$)**	**Simulated value ($\overline{S}$)**	**Error rate**
Monthly average airfare	343,7889286	339,770814	0,011687737
Monthly air passenger demand	54.239.240	54.087.453	0,002798481
Monthly number of flights	747.616,46	747.708,13	0,00012261

Source: own table

Respecting the error rate of 0.05, the model structure of the stock-flow diagram is considered quantitatively valid as all considered variables have an error rate below 0.05. Hence, the model is evaluated qualitatively and quantitatively valid.

The interpretation of results and the acceptation or rejection of the hypotheses are considered within the following section.

5 Risk Mitigation and Managerial Implications

As the model structure of the stock-flow diagram has been verified by the literature and the quantification of the model, the evaluation of results will be assessed in accordance with the hypotheses, which can be obtained from below.

H_{1A}:	*Commodity risks moderately has a positive effect on costs, hence influencing airfares.*

H_{1B}:	*Commodity risks moderately has a negative effect on costs, hence influencing airfares.*

H_{1C}:	*Strong correlation between risk and airfares have an impact on capacity forecasting.*

The rejection of hypothesis H_{1B} has already been considered in the previous subchapter, as the result of the correlation analysis of the jet fuel costs p.g. and the jet fuel spot price p.g. (M) shows a strong positive correlation along with 94% of the jet fuel costs p.g. being explained by the jet fuel spot price p.g. (M). Furthermore, the first part of the hypothesis H_{1A} has been accepted through the correlation analysis, and with respect to the results from the model simulation of the stock-flow diagram, it can be fully accepted. Concerning the hypothesis H_{1C}, a strong correlation between the jet fuel spot price p.g. (Q) and the average quarterly airfare was not identified as the coefficient of determination solely results in 47% of the average airfare's movements being explained by the jet fuel spot price p.g. (Q). Nevertheless, the impact of the change in jet fuel costs on the average airfare, which has been estimated through the jet fuel spot price, was verified through the stock-flow diagram. Hence, the impact of risk on capacity forecasting is considered valid. The lack of a significant correlation between the average airfare and the jet fuel spot price might be reasoned through the quality of the used dataset, which solely considers quarterly average airfares within the domestic US market. Thus, an analysis with a different dataset might lead to different results regarding correlation. However, regarding this investigation procedure and the used dataset, the hypothesis H_{1C} cannot be wholly accepted.

Furthermore, the deviations within the comparative analysis of the actual and simulated values, which are illustrated in Figure 19 to 21 should be further elucidated. The enormous deviations occur, when the change in fuel spot price increases or decreases rapidly, which was specifically the case within and after the fiscal crisis in 2007/2008. Thus, it is assumed that airlines tend not to pass on extreme cost changes to airfares but solely rather small changes in price. Although, it would reduce an airlines risk to extreme price swings. However, it would further lead to a reduction or rise in demand by reason of the airfare impact, and consequently, the airline would have to deal with increased under- or overcapacity. Therefore, other risk mitigation measures need to be considered to deal with extreme price swings. Referring to the literature review discussed in the theoretical section of Part 1, Morrell (2009) states that airlines have three options to minimize their exposure regarding fuel price volatility. Besides passing on costs to the passengers as it has been considered in the thesis' model, airlines could aim for an increase in fuel efficiency as well as jet fuel hedging via the physical or derivative market. Concerning the issue of fuel efficiency, it is dependent on several factors. The most crucial factor relates to the improvement of aircraft engineering. However, the renewal of the aircraft fleet is highly capital intensive and is additionally related to massive sunk costs in terms of disposal costs of old aircrafts or maintenance costs of additional ones. Even though leasing of aircrafts might be a further option as it is not as capital intensive, the principle of sunk costs still applies. Furthermore, the procedure of operations and in particular regarding the infrastructure and operational procedures at airports result in additional inefficiencies, which account for nearly 5% of extra fuel burn (IATA Economics 2017: 4). Besides long-term supply contracts with major oil firms, which include clauses concerning price adjustment in line with world market price movements, the risk exposure can be minimized through future or forward contracts as well as derivative instruments considering options, swaps, and collars (Morrell 2009: 190). Here, the choice in the type of hedging product depends on the airline and its risk averseness.

Considering the variety of options of risk mitigation measures, airlines should strive for diversifying measurements as much as possible. Due to the nature of specifically financial mitigation tools, which could lead to additional losses, diversification ensures usage of the maximum potential of risk mitigation. Therefore, all three of the options mentioned above should be considered within airline risk management. However, passing on costs to the customer is only possible to a certain extent due to its impact on capacity demand.

6 Conclusion

Resuming the elaboration of the paper, it can be endorsed that the impact of quantitative risk factors lies beyond the perception of risks within the airline industry. The dynamic structure of the system dynamics framework discloses the interdependencies of a significant variety of variables regarding commodity risk and capacity forecasting.

The hypotheses have been based on a causal feedback loop diagram, which is derived from the notion of system dynamics. There, the interrelations have been assessed through connecting arrows as well as positive and negative dependencies. This established the primary relations of the influencing dynamics of capacity management which have been reviewed on an individual basis in the literature review.

Furthermore, the base model has been developed from there on by using the approach of the stock-flow diagram, which deepens the aspect of interdependencies of capacity forecasting variables and commodity risk. These interdependencies have been described further through mathematical equations and evaluated through a dataset regarding the domestic US airline market.

The stock-flow diagram has been tested for the following hypothesis: The first hypothesis stated, that commodity risk effects cost positively and hence, airfares, has been accepted through the validation process via the correlation analysis and the dynamic model simulation. However, the second hypothesis had to be rejected because of accepting the first one. Furthermore, the third hypothesis was not fully accepted due to the first part assuming a strong correlation of commodity risk and airfares. The correlation analysis of the quarterly average airfare and the jet fuel spot price p.g. (Q) does not imply an explicit statistical significant result, although the dynamic model simulation by the stock-flow has been declared valid based on a qualitative verification through the literature review as well as a quantitative verification through the error rate approach. Furthermore, the comparison of the simulated values with the actual values from the used dataset identified the reasons for the significant missing correlation of the change in jet fuel spot prices and airfares. Solely minor changes in price are passed on to the customer, while extreme price swings are not incorporated. Nevertheless, the passing on of rising costs to the passengers is suggested a risk mitigation tool along with improving fuel efficiency, and the use of jet fuel hedging.

Overall, the research aim has been fulfilled through proofing the existing impact of commodity risk on airfares and hence, the impact on capacity forecasting. However, further research could be pursued involving more related influencing factors in the capacity forecasting approach as well as investigating the practical application of incorporating risk management into the capacity forecasting approach for individual airlines.

References

Bala, B. K.; Arshad, F. M.; Noh, K. M. (2017): System Dynamics. Modelling and Simulation. Singapore : Springer Singapore (Springer Texts in Business and Economics).

Barlas, Y. (1996): Formal aspects of model validity and validation in system dynamics. In: System Dynamics Review, vol. 12 (1996), No. 3, pp. 183-210.

Barnhart, C.; Belobaba, P.; Odoni, A. (2009): The Global Airline Industry. [Elektronische Ressource], Chichester : Wiley; American Institute of Aeronautics and Astronautics, Inc (Aerospace Series, vol. 23).

Barnhart, C.; Fearing, D.; Odoni, A.; Vaze, V. (2012): Demand and capacity management in air transportation. In: EURO Journal on Transportation and Logistics, vol. 1 (2012), No. 1-2, pp. 135-155.

Belobaba, P.; Simpson, R. (1992): Competitive fare and frequency effects in airport market share modelling. In : Journal of Air Transport Management (1992), No. 2, pp. 33-45.

Bureau of Transportation Statistics (2018): Airline Fuel Cost and Consumption (U.S. Carriers - Scheduled) (https://www.transtats.bts.gov/fuel.asp). Accessed on 21.01.2021.

Cronrath, E.-M. (2018): The airline profit cycle. A system analysis of airline industry dynamics. Abingdon, Oxon, New York, NY : Routledge (Routledge studies in transport analysis, vol. 8).

Forrester, J. W.; Senge, P. M. (1978): Tests for Building Confidence in System Dynamics Models. System Dynamics Group, Sloan School of Management, Massachusetts Institute of Technology (D (Sloan School of Management. System Dynamics Group)).

IATA Economics (2017): Economic performance of the airline industry (https://www.iata.org/en/iata-repository/publications/economic-reports/economic-performance-of-the-airline-industry---end-year-2017-update/). Accessed on 21.01.2021.

Keller, G. (2012): Managerial statistics. 9. ed., internat. ed., Andover : Cengage Learning.

Koopmans, C.; Lieshout, R. (2016): Airline cost changes. To what extent are they passed through to the passenger? In: Journal of Air Transport Management, vol. 53 (2016), pp. 1–11.

Mack, R.; Jiang, H.; Peterson, R. M. (2013): A Discussion of the Capacity Supply. Demand Balance within the Global Commercial Air Transport Industry. (http://www.boeing.com/resources/boeing-dotcom/commercial/about-our-market/assets/downloads/AirTransportCapacitySupplyDemand-Balance.pdf).

Morrell, P.; Swan, W. (2006): Airline Jet Fuel Hedging. Theory and Practice. In: Transport Reviews, 26. (2006), No. 6, pp. 713-730.

Morrell, P. S. (2009): Airline finance. 3. ed., reprinted 2009, Aldershot : Ashgate.

Sterman, J. D. (2000): Business dynamics. Systems thinking and modeling for a complex world. Boston : Mac Graw Hill.

Sterman, J. D. (2000): Business dynamics. Systems thinking and modeling for a complex world. Boston : Mac Graw Hill.

U.S. Energy Information Administration (2018): Monthly Spot Prices of Petroleum and other liquids (https://www.eia.gov/dnav/pet/pet_pri_spt_s1_m.htm). Accessed on 04.04.2018.

Appendix: Description of basic Mathematical Expressions

Mathematical expression	Name
$\overline{x}$	Mean
S_{xy}	Covariance
s_x	Standard deviation
r	Coefficient of correlation
R^2	Coefficient of determination

Source: own illustration

Authors

Prof. Dr Eyden **Samunderu** is a leading expert and trusted advisor in the area of air transport with extensive consulting experience at senior level. He currently holds a PhD in Strategic Management and is a Program Director at the International School of Management (ISM) in Dortmund Germany. He is also a Managing Partner at AMENA Africa Ltd and Board Advisor at Aviation Partners Africa [APA] London. His research interests include: air transport economics, multimarket contact, strategic group theory, competition dynamics, container logistics and maritime economics.

Yvonne **Küpper** is an Analyst at Innogy SE Dortmund focusing on Credit Risk Management. Her areas of research interest include air transport finance and risk management.

Friesendorf, Cordelia; Durai, S. Raja Sethu

Fisher Effect in Post-Unification Germany

Insights for Firms, Central Banks and Governments

Received 29.03.2021 · Received in revision 08.05.2021 · Accepted 08.06.2021 · Available online

Abstract

Irving Fisher's (1930) hypothesis is a pillar in international economic theory used by Central banks and financial ministries to assess the impact of real and nominal variables that are essential for firm-level growth. This paper examines the validity of generalized Fisher's hypothesis for post-unification Germany for the time-period beginning January 1991 until March 2020 through a frequency-time domain framework using continuous wavelet analysis. We make two inferences from the empirical analysis; first, the generalized Fisher hypothesis holds perfectly well for the study period. Second, the relationship between real stock return and inflation exhibited in the post-financial crisis period is attributed to the indirect growth effects of the Germany's overall domestic product. The results provide valuable insights for firms, banks and governments.

Keywords: Fisher hypothesis, real stock return, inflation, wavelet analysis, post-unification. JEL Classification: E43, E44

1 Introduction

1.1 Fisher's theory in the context of firms, banks and government

Firm-level management focusing on areas of company strategy and investor outlook undertakes business decision-making drawing from the macroeconomic developments in the domestic and international markets. For these purposes, the essential macroeconomic indicators in use at the firm-level include the growth of gross domestic output; the level of change in the general price level in producer, consumer and savings or investment rents; the developments in the exchange rates; and, the performance of the stock markets. Irving Fisher's hypothesis builds on the value of using real economic variables as against nominal values that are construed in currencies that further depend on free-float or fixed-rate regimes that may introduce fallacious decision-making of various economic factors that may result in a decline in profitable or economic well-being.

Accordingly, his hypothesis combines the macroeconomic variables of real stock return that indicates shareholder behavior and mood of the stock markets with that of inflation to make statements on the movement in domestic and international economic output that is the sum of agricultural, industrial and service sector production. Specifically, Fisher postulates a causal movement between the variables: real interest rate, nominal interest rate and expected inflation such that nominal interest rate influences changes in the inflation rate of a given market. Fisher's method is embedded knowhow used by listed companies and SMEs alike to get realistic insights on company growth besides operational planning of procurement, production and sales.

From the perspective of central banks and financial intermediaries, the Fisher hypothesis provides details on the correlation between inflation and interest rates so that production boosting or expansionary monetary policies can be planned by using open market operations that aims towards inflation targeting while providing consumer-friendly nominal interest rates. Central banks directly influence the flow of capital of wholesale and retail banks and together they have significant impacts on macroeconomic growth, which is steered by the government using fiscal expenditure policies. Fisher effect therefore demands a close working of monetary policies set by Central banks and macroeconomic policies implemented by federal governments to together create an environment that leads to high productivity, output and employment.

The Fisher effect is a well-researched field covering testing of fit primarily in the American markets. Overtime, the analyses has spread to different region to verify the validity and to identify the causes for non-congruential relations or gaps. In terms of methodology, there are considerable advances made especially in the univariate testing models often used in inflation-targeting under monetary policy initiatives. To name a few: the usage of the Augmented Dickey Fuller test (ADFL), the Kalman-Fitter Method and multiple versions of quantile cointegration (Asemota/Bala 2011; Atkins/Coe 2002; Bonham 1991) are predominantly in use both in long-run and short-run analyses of the Fisher theory. It needs to be stated that most studies address the veracity of the Fisher hypothesis and often in the context of monetary policy-making and currency-setting.

In the field of literature concentrating on Europe, Fisher studies are available on different sovereign governments or groupings of nations. Few studies address political events that have a massive impact on the economic-setting and result in a complete transformation of firm-level, banking and government incentive structures. Fisher studies on Germany are limited in literature; furthermore, there is none that cover the post-unification German nation, which is a historic event that affected all sectors of business and economic welfare. The next section discusses the ensuing of events that capture the impact of post-unification to help comprehend the importance and role of this phenomenon in the context of Fisher's theory.

1.2 Post-unification Germany: structural progress and viability for Fisher analysis

The economic and political union of East and West Germany was sealed in 1990 by creating market economy for free trade in goods and services and a free flow of resource mobility such as labor, capital and knowhow. Empirical evidence shows that despite a shaky start, market convergence lead to unprecedented structural changes that catalyzed increases in factor productivity and fueled trade integration, following surges in capital inflows and outmigration (Burda/Weder 2017). Although convergence or market integration did not represent a uniform distribution of profits or welfare, despite common legal frameworks, standardization, language and culture, neoclassical growth patterns could be verified in the overall growth of the output and the proliferation of businesses into the East (Burda/Weder 2017).

Empirical analysis in the post-unification period is rare, since reliable national income and product was unavailable until Akerlof et al. obtained sensitive information from the former East (Akerlof 1991). According to their estimates, 80% of industrial output was uncompetitive when valued at world prices in 1990, while physical production had collapsed by more than 50% and unemployment was over 20%. Firstly, the pumping in of fresh capital via direct subsidies and social funds; secondly, the West German influence of entrepreneurial ideas that enabled technology transfers and institutions that created a strong market-orientation together accounted for 2 trillion Euros of investments in the East. These inevitably contributed to the boom in retail and wholesale trade, logistics, and business services such as restaurants, entertainment and other personal and professional services (Akerlof 1991; Sinn 1991, 1995, 2002).

Notwithstanding these positive outcomes, expenditures grew for example, from 1990 to 1997, the overall social security burden rose from just under 30% to 36.3% (Sinn, 1992). Till date, East-West income, opportunity and private investment disparities exist, however all 16 federal states have jointly enjoyed an increase in the per capital GDP. Using Solow-Swan growth models, Burda/Weder (2017) establish a clear relationship between investment activity an individual growth rates of federal states resulting from high capital accumulation, such that the new states grew the fastest. Economic convergence estimated by various studies ranged between 2 and 4%. While total factor productivity was the highest immediately after unification, this dipped after 1995 indicating labor market disparities that have slowed down market convergence (Burda/Severgnini 2015).

Studies conclude that the post-unification Germany represents tedious and expensive convergence or market integration efforts primarily driven by labor and capital migration, but all conclude that this historical event represents a success to the extent that real economic variables such as interest or growth rates are disparity-free. This fact serves as the central motivation for this paper: converged or integrated markets provide the perfect basis for the verification of the Fisher analysis. The following section discusses the objectives of this study.

2 Objectives of the study

Studies on post-unification Germany show that the economic unification or the East-West convergence of factor and output markets, despite uniform laws, institutional frameworks, and investment levels, represented an unqualified success (Burda/Weder 2017). Despite 30 years of market integration, factor and output price disparities prevail. Many of these are attributed to the gradual structural integration, but the social problems such as continued outmigration are explained due to political and cultural differences as compared to the older federal states. Moreover, significant differences in productivity and unemployment rates continue to sustain the East-West economic performance, even though per capita consumption has increased (Franz/Steiner 2000).

Figure 1 captures the results of economic and institutional integration by comparing macroeconomic indicators of per capita gross domestic product, unemployment rate and gross annual income between western and eastern Germany for the years 1991 and 2019. The illustration supports the arguments made in German economic literature that markets integrated sufficiently.

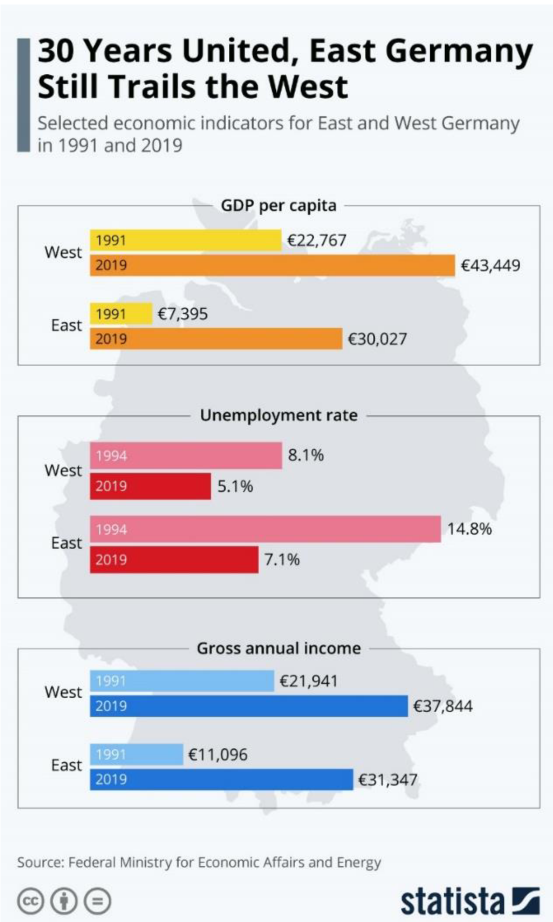


Figure 1: *Selected economic indicators for East and West Germany*
Source: *Statista 2020*

Notwithstanding these, the overall development of the post-unification in Germany is argued in the literature (see section 1.2.) to represent an imperfect yet a clear success. Furthermore, the case can be made that every country has regions or states, which are more prosperous than others due to comparative resource advantages – therefore a normal distribution of income or productivity can be allowed for as in any country analysis. This aspect, along with the economic progress made so far allows for post-unification Germany to be a viable country for the verification of the Fisher effect. Additionally, the following characteristics of old and new German states, which are similar to Anglo-Saxon federal frameworks as in the USA or the UK, support the Fisher-verification for the post-unification period:

Firm-level activity: German firms of varying legal forms and sizes operate throughout Germany. Local firms face zero regulation that deter labour, capital or innovation movement

Central bank's monetary policy: all states are governed by the German Central bank, namely the Bundesbank, that implements one unitary monetary policy for all states in coordination with the supranational Central bank, the European Central Bank. Likewise, all financial institutions like the Frankfurter Wertpapierbörse, EUREX and private banks are sources of financing for all states without discrepancies.

Governance structures: old and new states fall under the aegis of the federal government and have the same taxing and expenditure relationships. New states benefitted from extra financing from the old states but this policy is expected to be reversed. This does not present any problems for conducting the Fisher analysis.

The objectives of this paper are to validate the generalized Fisher hypothesis, using a data set for the period between January 1991 to March 2020 on stock returns, output, and inflation for Germany. First, we use a simple correlation to analyze the Generalized Fisher Hypothesis. Following this, in the next step we use a novel tool known as the continuous wavelet transformation method to identify any coherence between the variables stock returns, output and inflation to understand whether the hypothesis holds for post-unified Germany. If the hypothesis holds in both methods, we can verify Fisher analysis as a positive or affirmative phenomenon in Germany. Affirmative results would validate a high-level of market convergence such that firms, the Bundesbank and government institutions are working in a coherent manner that allows for free flow of information, ease of firm-level decision-making and overall economic stability.

3 Literature review

Fisher analysis is one of the oldest theories of modern monetary economics as a result of which there is around ninety years of literature covered by economists from different fields for multiple countries. For this reason, we classify literature into three sub-sections beginning with an explanation of what empirical behavior can the researcher expect, following a discussion of affirmative and country-based studies that have assessed Fisher's theory so far.

3.1 Empirics of Fisher's hypothesis

Economists have verified real stock returns' behavior over long horizons and its relationship to inflation and output. Fisher's (1930) seminal work purported that interest rates, especially the nominal rate, capture all information available in the market on future price increases. Consequently, the nominal interest rate and expected inflation having a one to one relationship, while real interest rate and expected inflation are mutually independent variables. Fisher's hypothesis is extended to other real asset returns, particularly to stock returns, and termed as Generalized Fisher hypothesis that is now a central topic in macroeconomics since it helps ascertain the efficiency of capital markets in relation to increases in purchasing power. The generalized Fisher hypothesis's central argument is that common investors are, on average, compensated for the value loss of purchasing power due to expected inflation. This is an important contribution to economic and business sciences since it explains the mandatory relationship in stakeholder behavior based on nominal price incentives.

3.2 Affirmative literature

Principal evidence as hypothesized by Fisher was provided by Nelson (1976) and Fama and Schwert (1977), where they show that an inverse relationship exists between real stock returns and inflation. Feldstein (1980) provides the explanation that taxation based on depreciation and capital gains can be impacted by prevalent inflation other studies inferred that the relationship remained unclear or invalid due to measurement errors or intrusion from other variables. Fama (1981, 1990) verified Fisher's theory to conclude that the inverse relationship resulted from the positive relationship between total economic activity and share price movement. Overall, Fama's argumentation and elucidation of Fisher has influenced most of the affirmative literature. For example, on these lines, Carmichael and Stabbing (1983) pointed out that the Fisher effect depends on the accurate measurement of inflationary expectations. It is to be noted that the original Fisher equation includes inflation expectation, henceforth it is appropriate to use a variable that adequately measures inflation expectation. Given the difficulty in obtaining accurate inflation expectation data, most empirical literature studies resort to using actual inflation data if the inflationary expectations are well anchored (Macdonald/Murphy, 1989; Gallagher/Taylor, 2002; Weidmann 2019).

Other studies address the methodological consideration of which variables to include to filter out the existence of Fisher effect. Darby (1975) posited that unaccounted taxation might provide misleading results, while Mishkin (1992), Gilbert and Yeoward (1994) argue the relevance and usage of short-term versus long-term interest rates in the analysis of the Fisher hypothesis. From those studies that verified

Fisher, Fama (1981) provided the most accepted proxy hypothesis inference by positing that the negative and positive relationship of output with inflation and stock returns, respectively, leads to incoherence in the Fisher effect.

3.3 Country-based verification

Most Fisher effect studies focus on USA's inflation-targetting initiatives. Malliaropulos (2000) and Million (2004) evaluated Fisher effect for the USA to check trend stationarity using vector autoregressive (VAR) and cointegration tests and concluded that Fisher holds in the medium and long terms. Studies evaluating Fisher for the Asian region demonstrated that Fisher held in Hong Kong, China, Korea, Singapore, Thailand and the Philippines (Ahmad 2010). Granville and Mallick (2004) conducted a long-term study of the Fisher Theory for the UK using annual data for the period 1900 to 2000 adopting Johansen cointegration tests with the result of significant validation. Other similar methodical validations can be found for: the Turkish economy by Incekara et al. (2012); a combined study of USA, UK and Japan by Toyoshima & Hamori (2011); and, an examination of Fisher for OECD countries that also assessed the connection between current and expected inflation (Pelaez 1995).

There are segregated studies on the EU. In Germany's case, Weidman (1997) tested the Fisher hypothesis for the time-period 1957-1991 and found that the nominal interest rate and inflation moved with less than one coefficient, implying partial validity. Piccinino (2011) analyzed the Fisher effect for the Euro area for 1999-2001 using the European interbank offered rate as the interest rate, and German Federal Securities to measure expected inflation validated the hypothesis. They demonstrate a thorough validation of Fisher's theory for the entire data-set using the Box-Jenkins methodology. Jung et al. (2014) analyzed the Fisher relationship using autoregressive methods with the conclusion that the analysis was inconclusive for Germany and attributed the reason to the impact of German unification. Overall, few studies have covered Germany's post-unification period for verifying Fisher, which is the literature gap we seek to fill with this study.

In the vast empirical literature examining Fisher's effect, there are conflicting inferences on the negative relationship between real stock returns and inflation. This paper focusses on the country-studies that have relied on affirmative results of the hypothesis. Methodological validation of the literature discussed above verified Fisher causality for time-series and panel data using uni-directional and two-way cointegration techniques. Few studies used Box-Jenkins and Johansen methods. We pioneer the usage of the thus-far untested tool - continuous wavelet analysis -, that is gaining ground for enabling an accurate, timely and effective explanation of time-series data. In the next section, we discuss the details of the data and the method employed.

4 Data and Methodology

4.1 Data

We use monthly data beginning from January 1991 to March 2020 on the variables: Dax Performance Index, Consumer Price Inflation, and Output in the production sector. The data for these variables are collected to represent the items: stock return, inflation, and output, respectively. Historical data on Dax Performance Index is compiled from Yahoo Finance (finance.yahoo.com), while for the variables inflation and output, we collected corresponding data from Deutsche Bundesbank (www.bundesbank.de). We constructed two sets of variables for the analysis; first, the monthly change of these variables and second, the annualized change of these variables to derive stock return, inflation, and output growth. The real stock return calculated as the difference between the stock return and inflation. We provide a detailed discussion of the method in the following section.

4.2 Methodology

Following Aguiar-Conraria et al (2011), this study uses the Continuous Wavelet Transformation to understand the relationship between real stock return, inflation, and output growth. The Wavelet Coherency is used to find out the coherency between two variables for different frequencies over time. Furthermore, we apply partial Wavelet Coherency to determine the coherency between two variables conditional upon other variables for differing frequency over time. The wavelet coherence gives us a localized correlation coefficient in time and frequency space, and the statistical significance of it is verifiable using Monte Carlo Simulation methods. Information on positive and negative co-movement is identified using the lead-lag relationship in the wavelet phase. Based on the elaboration provided in Aguiar-Conraria and Soares (2011), we capture the methodical description below.

For a set of two-time series $x(t)$ and $y(t)$, the derivation of Wavelet Coherency involves three steps: First, is to carry out the continuous wavelet transformation of these time series, which decomposes the series into a time–frequency space where oscillations can be observed from the wavelet power spectrum of a time series. The wavelet power spectrum can be interpreted as a measure of the local variance for a time series at each frequency. Wx (τ, s) and Wy (τ, s) are the wavelet transform of $x(t)$ and $y(t)$, while |Wx (τ, s)|2 and |Wy (τ, s)|2 are the wavelet power spectrums of these series, for time domain τ, and frequency domain s.

Second, the cross-wavelet transform of $x(t)$ and $y(t)$, is expressed as a product of the continuous wavelet transform of these series, which is similar to the covariance of these series in a time–frequency space where oscillations can be observed from the cross-wavelet power spectrum of these series. The cross-wavelet power spectrum depicts the local covariance of $x(t)$ and $y(t)$ at each time and frequency and denoted as |Wxy (τ, s)| = Wx (τ, s) Wy (τ, s).

Third, using the cross-wavelet and the wavelet power spectrum, the wavelet coherency, which is analogous with the correlation coefficient in the time and frequency domain, can be computed as presented below. In other words, for a set of two-time series *x(t)* and *y(t)*, the Wavelet Coherency is denoted as follows.

$$R_{xy}(\tau, s) = \frac{|S(W_{xy}(\tau, s))|}{\sqrt{S(|W_x(\tau, s)|^2)S(|W_y(\tau, s)|^2)}} \; with \; 0 \leq R_{xy}(\tau, s) \leq 1$$

Equation 1

The time-domain wavelet is given by, while the frequency domain is provided by s. W_x and W_y are the wavelet transform of *x* and *y*, respectively. S denotes a smoothing operator in both time and scale; without smoothing, coherency would be identical across all scales and times. On the same lines, the partial wavelet coherency, using an additional time series variable *z(t)* as a control variable is derived as follows:

$$R_{xy/z}(\tau, S) = \frac{\left|R_{xy}(\tau, S) - R_{xz}(\tau, S)R^*_{yz}(\tau, S)\right|}{\sqrt{(1-(R_{xz}(\tau, S))^2)}(1-(R_{yz}(\tau, S))^2)}$$

Equation 2

Further, we also construct phase difference between two time series to illustrate positive or negative correlation and lead–lag relationship between these two time series. The value of the phase difference between x(t) and y(t) ranges from − π to π. If x(t) and y (t) move together (in Phase) which is analogous to positive correlation at the specified time frequency if the phase difference is zero or it is between 0 and π/2. The reverse is true (out-Phase) when the phase difference lies between - π/2 and 0. The results from the estimated wavelet coherency are illustrated as graphs figures 2, 3, 4 and 5.

In the graphs, the thick black contour around the red color indicates the 5 percent significance level, estimated from Monte Carlo simulations using phase-randomized surrogate series. The colour code for coherency ranges from Blue (low, close to 0) to dark red (high, close to 1). Arrows are used to indicate the phase-difference between the two series. Furthermore, arrows pointing to the right or upwards indicate that the variables are in-phase. While arrows pointing to the left indicate that the variables are out of phase.

5 Discussion of Empirical Results

We start with a simple correlation to analyze the Generalized Fisher Hypothesis between the real stock return and inflation. The correlation coefficient between real stock return and inflation stands at 0.041 and -0.020 for monthly and annualized returns, respectively. Close to zero correlation indicating a near-exclusive nature of these two variables and supporting the Fisher hypothesis. The results from the wavelet coherency help us to understand this relationship with much clarity. The wavelet coherency output is in graphs where the period in months measures the long-run and short-run coherency between the variables. The high coherency indicated by the red color, and the significance level identifies with the black and grey border.

(a) Monthly Return **(b) Annualized**

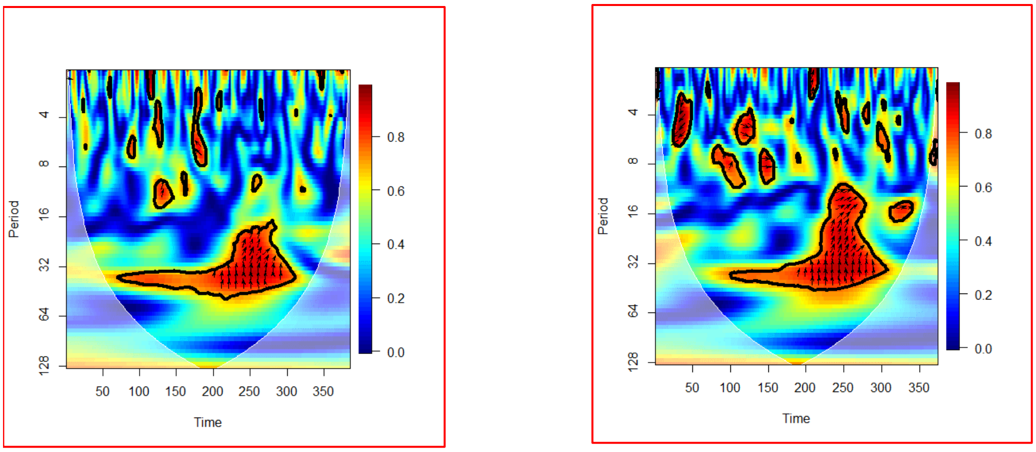


Figure 2: *Wavelet Coherency between real stock return and inflation*
Source: *own illustration*

Figure 2 provides the wavelet coherency between real stock return and inflation for both monthly and annualized returns, indicating that the coherency is more for the frequency period in the range of 16 to 64 months with a prominence during and after the global financial crisis period 2007-08. To examine the reason for this significant coherency between real stock return and inflation, we test Fama's hypothesis. This hypothesis's main idea is that the output acts as a proxy between real stock return and inflation towards establishing this relationship. In our case, since the correlation between real stock return and inflation is very low, and in the wavelet coherency, the effect is more prominent after the global financial crisis period, we are going to examine whether the output is acting as a proxy or not in this relationship.

Figures 3 and 4 plot the wavelet coherency between output growth with real stock return and inflation.

(a) Monthly Return **(b) Annualized Return**

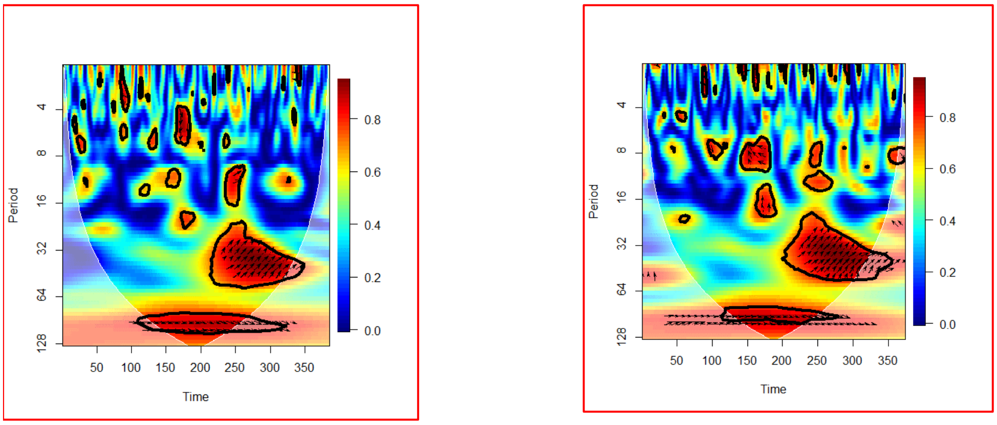


Figure 3: Wavelet Coherency between real stock return and output growth
Source: own illustration

(a) Monthly Return **(b) Annualized Return**

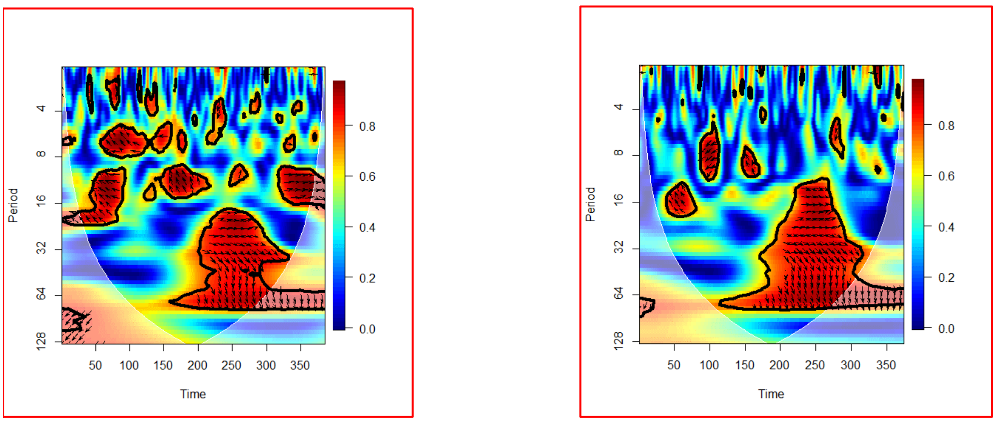


Figure 4: Wavelet Coherency between inflation and output growth
Source: own illustration

The graphs indicate that real stock return and output growth have a significant long-term relationship over the period; it also has a medium-term relationship during and post-global financial crisis period. Similarly, inflation and output growth have also shown a strong medium to a long-term relationship with a strong presence after the global financial crisis period. These analyses indicate the relationship highlighted by Fama in his proxy hypothesis. However, to obtain a complete and thorough overview, we ran a partial wavelet coherency to analyze the connection between real stock return and inflation. We explain the correlation between these variable as representative of the effect of the interaction of output growth on these variables, which is in line with Fisher's empirics. Figure 5 depicts the partial wavelet coherency, and it clearly shows that the real stock return and inflation are mutually exclusive variables as hypothesized by Fisher.

(a) Monthly Return **(b) Annualized Return**

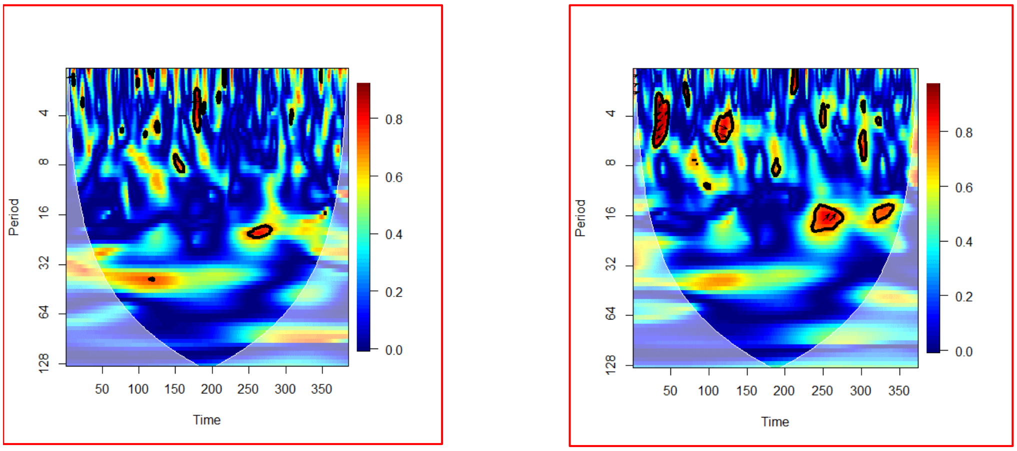


Figure 5: *Partial Wavelet Coherency between real stock return and inflation with output growth*
Source: *own illustration*

6 Conclusion

Management and financial decision-making draws on the stability and growth of macroeconomic variables, notably output and stock returns. Time-tested macroeconomic theories such as Fisher's hypothesis help verify and establish the interrelation between these variables in tandem with the growth in price-levels. Our study contributes to this long-standing field of research in two ways: 1.) by using the novel method of wavelet analysis; and, 2.) by applying this method to post-unification Germany for the first time. We use monthly data from January 1991 to March 2020 to examine the Generalized Fisher Hypothesis.

Our results using simple correlation analysis to wavelet coherency as well as partial wavelet coherency indicate that the Fisher hypothesis holds in post-unification Germany. In the process of analysis, we observed a coherency exhibited by real stock return and inflation during and after the global financial crisis period. We used Fama's proxy hypothesis for verification and conclude that the coherency is mainly an outcome of an interaction of the variables return and inflation with output growth.

Our study aligns with regular practice in Fisher verification in using annualized returns as estimators. In the wake of Blume's (1974) contentment with the practice of using annualized returns because these estimators may not be unbiased, and may rather overestimate output performance, we used monthly returns data to compare the results. We can thus conclude that our results are robust. Future research using wavelet analysis could investigate the existence of such a bias to verify if a different pattern emerges.

References

Ahmad, S. (2010): The long-run Fisher effect in developing economies. In: Studies in Economics and Finance, 27. (2010), No. 4, pp. 268-275.

Aguiar-Conraria, L.; Soares, M. J. (2014): The Continuous Wavelet Transform: Moving Beyond Uni- and Bivariate Analysis. In: Journal of Economic Surveys, 28. (2014), No. 2, pp. 344-375.

Akerlof, G. A.; Rose, A. K.; Yellen, J. L.; Hessenius, H. (1991): East Germany in from the Cold: The economic aftermath of currency union. In: Brookings Papers on Economic Activity, 22. (1991), No. 1, pp. 1-106.

Asemota, O. M.; Bala, D. A. (2011): A Kalman Filter approach to Fisher Effect: Evidence from Nigeria. In: CBN Journal of Applied Statistics, 2. (2011), No. 1, pp. 71-91.

Atkins, F. J.; Coe, P. J. (2002): An ARDL bounds test approach to testing the long-run Fisher effect in the United States and Canada. In: Journal of Macroeconomics, 24. (2002), No. 2, pp. 255-266.

Blume, M. (1974): Unbiased estimates of long-run expected rates of return. In: Journal of the American Statistical Association, 69 (1974), No. 347, pp. 634-638.

Bonham, C. S. (1991): Correct cointegration tests of the long-run relationship between nominal interest and inflation. In: Applied Economics, 23. (1991), No. 9, pp. 1487-1492.

Burda, M. C.; Severgnini, B. (2015): TFP Convergence in German States since Reunification: Evidence and Explanations. SFB 649 “Economic Risk“ Discussion Paper 2015-054. Humboldt University Berlin. (https://www.wiwi.hu-berlin.de/en/Professorships/vwl/wtm2/mitarbeiter-en/prof-michael-burda-phd/tfp-convergence.pdf). Accessed on 25.02.2021.

Burda, M. C.; Weder, M. (2017): The Economics of German Unification after Twenty-five Years: Lessons for Korea. SFB 649 “Economic Risk“ Discussion Papers SFB649DP2017-009, Sonderforschungsbereich 649, Humboldt University Berlin. (https://edoc.hu-berlin.de/bitstream/handle/18452/19408/2017-009.pdf?sequence=1&isAllowed=y). Accessed on 25.02.2021.

Carmichael, J.; Stabbing, P.W. (1983): Fisher’s Paradox and the Theory of Interest. In: American Economic Review, 73. (1983), No. 4, pp. 619-630.

Darby, M. R. (1975): The financial and tax effects of monetary policy on interest rates. In: Economic Inquiry, 13. (1975), No. 2, pp. 266-276.

Fama, E. F. (1981): Stock returns, real activity, inflation and money. In: American Economic Review, 71. (1981), No. 4, pp. 545-565.

Fama, E. F. (1990): Stock returns, expected returns, and real activity. In: Journal of Finance, 45. (1990), No. 4, pp. 1089-1108.

Fama, E. F.; Schwert, G. W. (1977): Asset returns and inflation. In: Journal of Financial Economics, 5. (1977), No. 2, pp. 115-146.

Feldstein, M. (1980): Inflation and the stock market. In: American Economic Review, 71. (1980), pp. 545-65.

Fisher, I. (1930): The Theory of Interest. Macmillan: New York.

Franz, W.; Steiner, V. (2000): Wages in the East German Transition Process: Facts and Explanations. In: German Economic Review, 1. (2000), No. 3, pp. 241-269.

Gallagher, L.; Taylor, M. P. (2002): The stock-return inflation puzzle revisited. In: Economics Letters, 75. (2002), No. 2, pp. 147-156.

Gilbert, C. L.; Yeoward, S. M. J. (1994): Is the Fisher Effect for Real? Evidence from the UK Real and Nominal Bonds. Department of Economics, Queen Mary and Westfield College. London. (Working Papers, 310).

Granville, B.; Mallick, S. (2004): Fisher hypothesis: UK evidence over a century. In: Applied Economics Letters, 11. (2004), No. 2, pp. 87-90.

Incekara, A.; Demez, S.; Ustaoglu, M. (2012): Validity of Fisher effect for Turkish economy: cointegration analysis. In: Procedia Social and Behavioral Sciences, 58. (2012), pp. 396-405.

Jung, C.; Shambora, W.; Kyongwook, C. (2007). In: Applied Economic Letters, 14 (2007), pp. 555-557.

MacDonald, R.; Murphy, P D. (1989): Testing for the long-run relationship between nominal interest rates and inflation using cointegration techniques. In: Applied Economics, 21. (1989), pp. 439-447.

Malliaropulos, D. (2000): A note on nonstationarity, structural breaks and the Fisher effect. In: Journal of Banking & Finance, 24. (2000), No. 5, pp. 695-707.

Million, N. (2004): Central bank's interventions and the Fisher Hypothesis: A Threshold Cointegration Investigation. In: Economic Modelling, 21. (2004), No. 6, pp. 1051-1064.

Mishkin, F. S. (1992): Is the Fisher Effect for Real? A Re-examination of the Relationship between Inflation and Interest Rates. In: Journal of Monetary Economics, 30. (1992), No. 2, pp. 195-215.

Nelson, C. R. (1976): Inflation and rates of return on common stocks. In: Journal of Finance, 31. (1976), No. 2, pp. 471-483.

Pelaez, R.F. (1995): The Fisher Effect: reprise. In: Journal of Macroeconomics, 17. (1995), No. 2, pp. 333-346.

Piccinino, S. (2011): An Examination of the Fisher Effect in the Euro Area. (https://ssrn.com/abstract=1909318). Accessed on 25.02.2021.

Sinn, H.-W. (1995): Factor Price Distortions and Public Subsidies in East Germany. London: Centre for Economic Policy Research. (CEPR Discussion Paper, 1155).

Sinn, H.-W. (2000): EU Enlargement, Migration, and Lessons from German Unification. In: German Economic Review, 1. (2000), No. 3, pp. 299-314.

Sinn, H.-W.; Sinn, G. (1991): Kaltstart: Volkswirtschaftliche Aspekte der deutschen Vereinigung. Mohr : Tübingen, Germany. (Also published in English as Jumpstart: The Economic Unification of Germany. MIT Press, 1992.)

Statista.com (2020): 30 Years United, East Germany Still Trails the West. (https://www.statista.com/chart/19903/economic-differences-between-eastern-and-western-germany/). Accessed on 25.02.2021.

Toyoshima, Y.; Hamori, S. (2011): Panel Cointegration of the Fisher Effect: Evidencefrom the US, the UK and Japan. In: Economics Bulletin, 31. (2011), No. 3, pp. 2674-2682.

Weidmann, J. (1997): New Hope for the Fisher Effect? A Re-examination Using Threshold Co-integration. University of Bonn. (Discussion Paper, B-385).

Weidmann, J. (2019): Expectations Matter, presented at the Joint Deutsche Bundesbank-Bank of France Conference on Household Expectations. Frankfurt am Main, 26 September 2019.

Authors

Prof. Dr. Cordelia **Friesendorf** is professor of economics and finance at the International School of Management (ISM) in Campus Hamburg. She holds a doctoral degree on European retail banking markets from the Jean Monnet Centre of Excellence of the Free University in Berlin. She received her professorship in 2011 and was Campus Head in Hamburg until 2019. She has more than 18 years of research and management experience having worked on finance and investment issues, multilateral policy-making and governance in the British government, Oxford University and Tata energy among others.

Prof. S. Raja Sethu Durai is Professor of Economics at the University of Hyderabad, India. He holds a doctoral degree in economics with a specialization in monetary economics from the University of Madras, India. He has more than 15 years of research and teaching experience including 3 years in industrial consulting and corporate research at GOIC, Doha-Qatar and GE Money-MSE Decision Sciences Lab, India. He has published more than 30 journal articles in highly reputed international journals and chapters in books in the area of macroeconomics and applied finance.

Edler, Ronja; Perret, Jens, K.

Who Influences the Influencer – First Approaches towards a Quantitative Influencer Marketing

Received 17.12.2020 · Received in revision 14.07.2021 · Accepted 01.09.2021 · Available online

Abstract

The present study revisits the topic of influencer marketing from a quantitative point of view. For a sample of 255 influencers from the field of women's fashion on Instagram the lists of those accounts they follow have been used to generate a network connecting them to their peers.

Based on core metrics for the influencers in the sample and the network itself, two research questions have been considered. Asking for a relative measure of the relevance of an influencer among her peer group, it has been argued that a single metric alone does not suffice. Thus, the eigenvalue centrality as a measure of an influencer's relative importance in the network of her peers is proposed complemented by the betweenness centrality as a quantitative approximation of an influencer's reach. Both concepts are shown to focus on distinctly different concepts and are used to propose a two-dimensional approach to rank influencers.

A secondary question regarding the clustering of influencers into national groups has been posed. While significant national clustering exists in the sample, so do links to influencers of different origins. Regarding cross-national links, it is particularly the highest ranked influencers that responsible for the major share of links. Nevertheless, the network of influencers in women's fashion clearly is of an internationally connected nature.

Keywords:

influencer, Instagram, women's wear, fashion, social network analysis, death of distance, social media

1 Introduction

While the term \`influencer´ and the related \`influencer marketing´ are relevant in the current marketing literature, the term itself is not unambiguously defined. Additionally, there is only a very limited number of publications covering the topic and providing a quantitative methodology (Arora et al., 2019; Bakshy et al., 2011; Mittal et al., 2020).

This study adds to the discussion of quantitative approaches to influencer marketing in two regards. First, it delivers an approach to quantitative influencer marketing that is based solely on Instagram core metrics and can be used to evaluate an influencer's importance and reach in relation to their peers and without the use of any exogenously defined rating model. Additionally, the so-called death-of-distance hypothesis is considered in an influencer-related context, considering the extent of international links between influencers.

To illustrate the points raised in this study, a sample of 255 influencers on Instagram that have their primary focus on women's fashion is considered. As all influencers included in this study are women as is the population of all possible influencers, a female pronoun is used throughout the remainder of this study.

Instagram is not only a well matured Social Media platform with a broad and still steadily growing user base (eMarketer, 2020) but as well a platform that is used by most of the established influencers from the segment of women's fashion. It is a platform frequented by young users – following the numbers published by Instagram (Instagram, 2018) more than 1 billion users worldwide use Instagram with more than 70% thereof being below 35. 85% of all teens - the main clientele of tomorrow (Piper, 2019) - state that they use Instagram on a daily basis.

The segment of women's fashion has been selected as it allows to generate a large enough sample without compromising the homogeneity of the sample or the respective population, while at the same time it is restricted enough to be represented decently enough by a sample of 255.

The main research goals of this study are providing a suitable quantitative methodological approach to study the phenomenon of influencers and thereby provide decision support for marketing managers active in influencer marketing. Furthermore, it focuses on the extent by which influencers from the considered segment are connected with each other and whether distinct clusters within the network can be detected. Thus, the question is answered whether sponsored postings only reach a local clientele or whether the potential exists that influencers influence each other and thus disseminate their opinions globally.

While the literature on quantitative influencer marketing is limited, the succeeding chapter aims at providing an introduction into the topic and anchoring this study and influencer marketing in particular in the field of affiliate marketing and thus digital marketing where it originated from.

Following the review of the theoretical foundation a brief introduction into Social Network Analysis is given motivating on the one hand the methodology implemented in generating the underlying network linking the sample of influencers and on the other hand the tools required to answer the underlying research questions which are:

RQ 1: How does an approach look like that allows for a network inherent, relative ranking of influencers and their further study?

RQ 2: Are there significant links between influencers from different nationalities, or do national clusters exist within the overall network?

Following the analysis itself, the study concludes with a summary of the results and conclusions to be drawn from them, as well as research options motivated by this study and limitations linked to it. Additionally, the potential use of the results of this study for marketers involved in influencer marketing are discussed.

2 From Affiliate to Influencer Marketing

Affiliate Marketing is part of the broader field of online marketing. Companies that sell products via an online platform pay a fee to the owner of a website, a blog or a social media channel to advertise their products in different ways to generate additional sales (Lammenett, 2017).

In either case the product or service to be advertised can be provided to a 'potential' affiliate for free, hoping for positive coverage, or a contract is set up between both parties detailing the obligations and the remuneration scheme for the affiliate.

With an increasing digital change and a merging or integration of different platforms, the digital sphere and here in particular the Social Media sphere developed as a primary target of marketing activities. While Social Media has already been present for about five decades, in particular since 1997 and the introduction of Six Degrees (Boyd & Ellison, 2007). Marketing's interest in Social Media, in particular in so-called influencers – actors in a Social Media platform that have a significant followership – only rose as a relevant aspect of Social Media marketing in the last ten years (Kozinets et al., 2010).

Combining the digital equivalents of affiliate marketing and product placement with the specifics of the digital and in particular the Social Media environment and new technologies like Social Shopping results in a first definition of what is currently understood as influencer marketing. For the aim of this study this first definition of influencer marketing suffices as its focus lies primarily on influencers as actors and less on the tools to interact with them.

However, a more in-depth introduction to influencer marketing can be found in Brown and Hayes (2008) or Nirschl and Steinberg (2018). As this study focuses on Instagram influencers, Veirman et al. (2017) provide a suitable introduction to influencer marketing on Instagram. While studies like Bakshy et al. (2011), Aswani et al. (2017), Arora et al. (2019) or Mittal et al. (2020) focus on other platforms like Twitter, Aggrawal et al. (2018) on YouTube or Cavalli et al. (2011) and Arora et al. (2019) on Facebook. Arora et al. (2019) is currently the only study using a quantitative approach on Instagram data trying to quantify an influencer's importance and studying their relations. Kim et al. (2017) have a similar focus as they consider the relations between influencers, their main objective, however, lies in describing the types of links between the influencers and in particular whether linked influencers also share followers. Another Instagram-based quantitative analysis is presented by Argyris et al. (2020) who study in detail the effects of the contents of Instagram posts. Through the use of a deep-learning algorithm, they furthermore illustrate the advantages of using machine learning approaches in the context of influencer marketing.

From a different perspective and not based on influencers' following data Haenlein et al. (2020) considers the potential and effectiveness of Instagram among other Social Media channels aiming primarily on the deduction of recommendations for practitioners. In a similar context, Jin et al. (2019) and (Jin et al., 2021) focus on the relevance of the trustworthiness of the influencer and Lee and Kim (2020) on the credibility.

However, no general and quantifiable definition of what constitutes an influencer exists, and all relevant studies define the term slightly different. A number of studies like Lim et al. (2017), Lou and Yuan (2018) or Audrezet et al. (2018) put the focus of their definitions on authenticity and the position of the influencers or their potentially large audience. On the other hand, Veirman et al. (2017) and Veirman and Hudders (2020) stress aspects like brand attitude. While terms like authenticity or brand attitude are hard to quantify, characteristics like followers, reach, posting frequency, engagement rate or growth rates are often quoted (Aggrawal et al., 2018; Bendoni, 2017; Hall, 2017) as tangible indicators of an influencers position. However, no consensus exists on relevant threshold values for these characteristics, which in consequence leads to a rather shallow distinction between nano-, micro- and macro-influencers. An additional downside of most of these studies available is that their measures are exogenously defined and do not result from the networks at hand, as is the case in Arora et al. (2019).

The definition for an influencer that is used in the course of this study and which is sufficient for all relevant purposes marks an influencer as a user of Social Media who on the platform under consideration sports at least 100,000 followers. Being termed an influencer in corresponding rankings and the relevant press adds a qualitative dimension to the used definition of an influencer. A distinction into nano-, micro- and macro-influencers does not take place as the study will focus on macro-influencers alone.

The present study aims to provide to the existing literature on influencer marketing in two ways.

The first goal of this study is to deliver a general approach to quantitative influencer marketing that is based solely on Instagram core metrics by evaluating the influencers in relation to their peers. This sets this study apart from comparable studies that evaluate influencers based on their general followership or exogenously defined scoring or rating schemes. In this regard it applies ideas as already proposed by Wu et al. (2013) and Lagrée et al. (2018) to the context of Instagram and diverges from approaches as used for example in Arora et al. (2019). Condensed into a single research question, the study tries to answer the question:

RQ 1: How does an approach look like that allows for a network inherent, relative ranking of influencers and their further study?

Second, studies like Lengyel et al. (2015) or Han et al. (2018) argue that the internet and thus a number of internet related activities like Social Media breach national borders and lead to an increasing global integration – in the literature, e.g. in the context of research and development and company cooperations this is also referred to as the death-of-distance hypothesis. This might particularly hold true for Social Media platforms, where nationality usually is not even visible. This study the revisits this hypothesis, however not on the basis of the general followership of an influencer but on the basis of her network of peers, though answering the following second research question:

RQ 2: Are there significant links between influencers from different nationalities, or do national clusters exist within the overall network?

3 Methodology and Analytical Framework

3.1 Data Source

255 influencers have been selected as a census of rankings that list the most significant influencers in women's fashion. Only those influencers were considered that additional fulfill the quantitative criterion of having at least 100,000 followers by the time of conception of the initial data set in early 2018. The rankings considered in the context of this study include Block - (Block, 2016), Collsen - (Collsen, 2016), Editorial Stuff - (Editorial Staff, 2016), Ferrari - (Ferrari, 2018), Forbes - (Forbes, 2018), Gushcloud - (Gushcloud Pte Ltd, 2017), Klein – (Klein, 2016)- and West - (West, 2017). A full list of the sampled influencers can be found in Table 7 in the appendix. This sampling method while not exhaustive incorporates an additional qualitative dimension that ensures an expert-based pre-selection. Considering the origin of the implemented rankings, a bias in the direction of US and German influencers is inevitable, but the data set as a whole can see be seen as representative for the population of influencers focusing primarily on the topic of women's fashion.

Not for every influencer it has been tested whether and by which share they have genuine or bought followers. However, them being part of an established ranking as well as selective testing hints that almost all of them have a significant followership, validating their presence in the sample.

For each of the influencers, based on their Instagram profile, data is collected in particular on their following lists but as well on other core metrics like the number of followers, the number of other users they follow and the overall number of posts. Due to the lack of a suitable API interface, all data had to be manually downloaded from the influencers' profiles. To assure that the collected data is not biased by time-dependent changes to the influencers' profile all data points have been collected over the course of only two weeks.

The following lists are used to generate a directed network of links between them. The following section illustrates the involved procedure in more detail.

Additionally, external data is collected on the origin of the influencers, which other topics aside from women's fashion they cover, their age and whether they officially list receiving sponsoring or are active as a model.

All 255 influencers are women that also are active at other Social Media platform and own either a blog or their own website.

3.2 Social Network Analysis

The term 'Social Network Analysis' summarizes all those methods that can be used to model, illustrate and analyze all types of social interactions and relations in a broader context.

A social network can be seen as a set of actors that are linked in a certain way. This allows for a multi-dimensional approach with regard to the actors as well as to the type of linkages.

The simplest type of network assumes all actors or nodes in the network to be comparable, and that only a single type of linkage or edge exists between any two nodes. This is also the type of network that is considered in the course of this study.

Using this simple approach to networks makes it possible to represent the network via a quadratic matrix, where an element of row i and column j describes the relation between nodes i and j. This matrix is called the adjacency matrix.

If the network is undirected, each relation is automatically reciprocal, e.g. being friends with someone, and the adjacency matrix is symmetrical. For directed networks, a relation is not necessarily reciprocal, e.g. followings on Twitter or Instagram, and the adjacency matrix usually is not symmetrical.

While in an undirected network the in-degree, the number of links that point to a node, the out-degree, the number of links that point away from a node, and thus the degree centrality as such are identical, the situation changes in a directed network.

This study focuses on Instagram as a social network, an inherently directed network. The nodes are different actors active on Instagram, whereas the edges are the follower and following relations the actors have with each other; the in-degree is the number of followers and the out-degree is the number of other actors one follows.

The simplest way to capture an Instagram network is thus to set all elements of the adjacency matrix to zero except where actor j follows actor i, the matrix will report a 1 in row i and column j. As only the relationship network of influencers with their peers is considered, the adjacency matrix reports a 1 in row i and column j if influencer i can be found in the following list of influencer j.

A more sophisticated approach to modeling the network would be to note in element $n_{i,j}$ the number of times actor j likes or comments on a post by actor i. Aside from the additional computational burden, this would add additional levels of complexity to the analysis as following, liking and commenting can be seen as three different dimensions that have to be treated separately. In this regard, the study focuses solely on the first type of following relations.

Furthermore, for established influencers, the in- and out-degree strongly deviate from each other. In the context of this study the in-degree, the number of followers, does not play a central role as only relations between the members of a select group of influencers are relevant here. Basing the analysis on the out-degree will achieve the same goal, but at a much lower computational burden.

While the main goal of this introductory study lies in mapping the links between selected influencers, additional measures from social network analysis like the eigenvalue centrality, the closeness centrality, the Katz centrality, the authority score or the page-rank allow for an analysis of the importance of different influencers. While this analytical approach has not yet found a foothold in the study of inter-influencer networks, studies like Wu et al. (2013) or Lagrée et al. (2018) use comparable measures to establish leaders in Social Media networks.

On the other hand, measures like the betweenness centrality or the hub score allow for an analysis of the relevance of an influencer as a potential transmitter of knowledge in the network (Newman, 2018).

With the four listed measures, first and foremost the eigenvalue centrality (as the other indicators are similar in nature and highly correlated to the eigenvalue centrality), as indicators of an influencer's relevance or importance a tool becomes available to classify influencers simply by looking at the relevance they play in the network of their peers. In the later course of the study, eigenvalue centrality will thus also be referred to as *Importance*.

Eigenvalue centrality as a concept is based on the fact that the size of an eigenvalue determines the importance of the corresponding eigenvector to generate the space containing all nodes, a concept that is implemented similarly in the context of factor analysis. Mathematically, the eigenvalues measure results from the eigenvalues of the adjacency matrix (Newman, 2018). The relevance of an influencer thus becomes network-endogenous, as compared to most qualitative studies on influencers or quantitative studies like Arora et al. (2019) that define an influencer's importance exogenously.

From a more medical point of view, Fletcher and Wennekers (2017) show for neural nets that eigenvalue centrality is correlated with the firing activity of neurons in the network, which means the introduction of new knowledge into the network; a process similar to the introduction of information via influencers. Translated into the context of Social Media networks, this means that knowledge or information introduced into the network by influencers associated with high eigenvalues will have the strongest impact on the other nodes in the network.

Simply put, influencing can be interpreted as the transmission of information from one party to another. Using the two indicators for an influencer's potential as a transmitter of knowledge or information, first and foremost the betweenness centrality (it is correlated with the other variables as well), shows a potential of the influencer that can, at least in part, be interpreted as an approximation to her Reach among her peers.

The concept of betweenness centrality has been introduced by Freeman (1977) and is continuously updated from a mathematical-technical point. The multitude of its practical applications in the context of Social Media networks in summarized in the study by De et al. (2020). Mathematically, it is calculated as the number of times that a node lies on the shortest path between any two other nodes; in most contexts this number is then normalized to the interval [0; 1]. Since the betweenness centrality describes an influencer's potential to transmit information, it thus fulfills the same function as the concept of an influencer's reach and will thus also be referred to as an approximation for the reach in later parts of the analysis.

In this context, the approach presented herein also endogenizes at least in part the equally relevant measure of an influencer's Reach, even if not necessarily among all the followers still among the peers.

4 Analysis

4.1 Description of the Data Set

Aside from the links between the influencers, i.e. their following lists, additional core metrics have been collected as stated in section 3.1; that is the influencers' number of followers, the number of accounts they follow and the number of posts up to the point of data collection. To complement the picture of the influencers, for each one the age as far as publicly available and their origin has been collected. If any of the influencers is listed as possessing two or more citizenships the one has been used that fits the influencers center of living the best.

Table 1 summarizes the means and medians as well as minimum and maximum values for the three core metrics and the age, while *Table 2* gives an overview of the distribution of origins of the influencers in the sample.

Table 1: Central Tendency of Core Metrics

Variable	Follower	Following	Posts	Age
Mean	1,158,753	662	2,969	26.5
Median	506,000	560	2,329	28
Minimum	107,000	30	113	16
Maximum	37,900,000	4,866	17,633	40

Source: Own table

Table 2: Origin of the Influencers

Origin	USA	Germany	Sweden	Spain	Italy	UK	Australia	Russia	Netherlands	Asia*	Rest
	77	70	18	14	13	9	8	7	6	10	23

*Asia including as well China, Japan and Singapore

Source: Own table

Considering that, all four metrics in Table 1 report a mean larger than the median shows they all are rightwards skewed; they contain more small than large values. This gives rise to the assumption that even among the top influencers in the field of women's fashion, a strict hierarchy exists with very few α-influencers on top; a phenomenon that is seen again in the following analysis below. Cha et al. (2010), Weng et al. (2010) and Bakshy et al. (2011) provide evidence of similar distributions regarding Twitter networks. Perret (2021) in the context of a panel-study and underpinned by a mathematical model provides strong evidence that this structure might be endemic across Social Media, or at least Instagram.

Since the sample consists only of already established influencers - 246 have one type of professional sponsoring or another and 202 own their own blog (all of them own a blog or a personal website) – the low average age of 26.5 years, with roughly one third of the sample of an age below 25, shows that an established standing on Social Media is not as age dependent as in many offline contexts.

The majority of the influencers stem from the US (30.19%) or Germany (27.45%) as seen in *Table 2*. While other regions are represented in the sample as well, considering that it is a sample of established influencers only the large share of Germans and the small share of French (1.96%) might surprise a bit. The large share of German influencers, at least in part, is due to the fact that some German influencer ranking have been used to build the sample.

To get a better feel for the data, it has been considered how the core metrics relate to each other. The number of followers that is usually considered the central figure in quantitative influencer marketing does not correlate significantly with any of the other three metrics. The correlation coefficient by Pearson and Bravais is $r = -0.0157$ for the followed, $r = 0.0873$ for the number of posts and $r = -0.0507$ for the age. All three aspects thus cannot be considered central impact factors on an influencer's relevance, if it is measured via her followers, which questions the usability of the followers as the single measure of relevance.

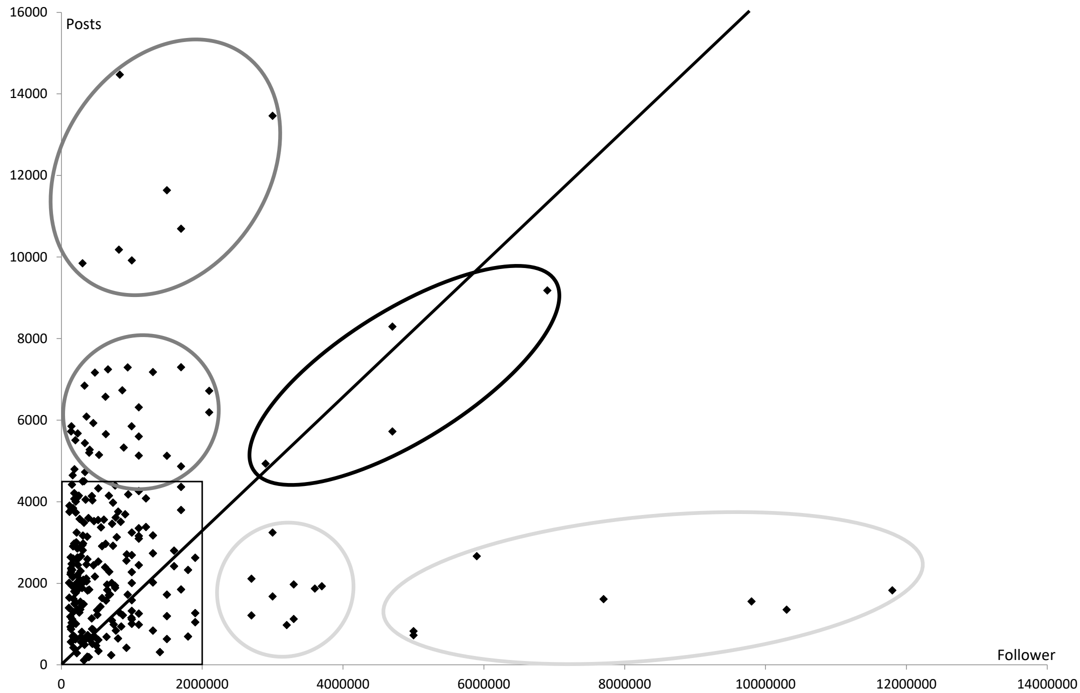


Figure 1: *Followers vs. Posts*
Source: *Own figure*

An additional interesting insight can be generated if follower numbers and posts are plotted against each other, as done in *Figure* 1.

The figure clearly shows that four more or less distinct groups exist. In the upper left area, the two dark gray ellipses describe over-performers who post comparatively much as compared to the under-performers in the lower right area. From a different perspective, the dark gray area could also be referred to, as those influencers that use a quantity-oriented approach to posting whereas the influencers on the lower right rather use a quality-oriented approach to posting.

The black ellipse in the middle shows those influencers who reach a relative equilibrium. However, the black box in the lower left is of particular interest since it contains roughly 80% of all influencers and those contained within show no relation of any type with a correlation of just r = 0.000 (p-value = 0.997). Note, that all stated correlations are rank correlations, since all considered variables are significantly different from a normal distribution.

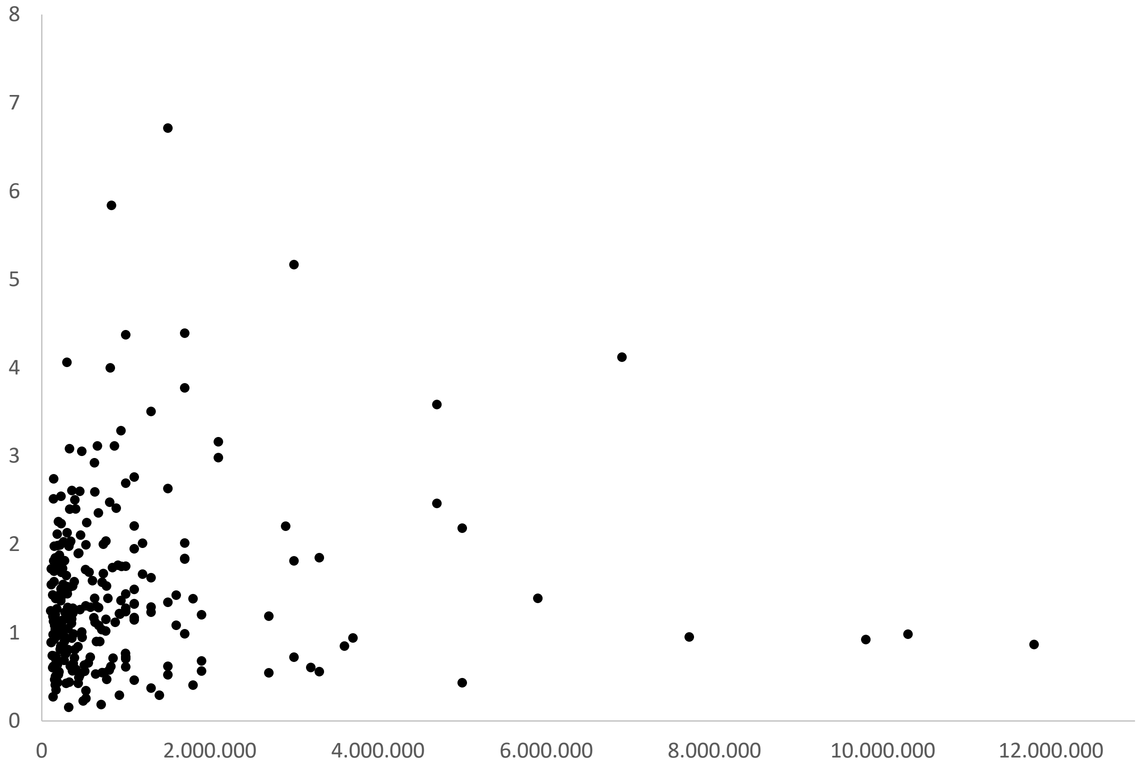


Figure 2: *Followers vs. Posting Frequency*
Source: *Own figure*

A comparable pattern can be observed for any combination of the metrics followers, followed and posts. In addition, the pattern only marginally changes if the number of posts is replaced by the average posting frequency – the number of posts divided by the time active on Instagram – taking into account that long-term members had more time to accrue posts. *Figure* 2 illustrates this relation – excluding Gigi Hadid with 37.9 Mio. followers and Arielle Noa Charnes with an average posting frequency of more than 45 posts per day. While the under- and over-performers became harder to be identified, the majority of influencers can still be found in a rather bounded area in the lower left of the figure.

Accounting for an influencer´s age in physical as well as in digital form is an important aspect to avoid biases in general, but major patterns still remain even if they are no longer as distinct. While the internet in general and Social Media in particular facilitate fast growth of certain persons' prominence, a longer time horizon in which they can actively work on their prominence and their image might increase just that. This argument is supported by a strongly significant (p = 0.000) positive correlation of r = 0.631 between the number of posts of an influencer and days active on Instagram. With a correlation of r = 0.5310 (p 0.000) the relation between physical age and posts is only marginally less pronounced.

4.2 A new approach for a network inherent, relative ranking of influencers

Applying the approach laid out in section 3.2 to the data set introduced in section 3.1 resulted in a network with 251 of the 255 influencers being linked to at least one other influencer. The four influencers that do not integrate into the network are Naomi Neo, Federica Nagi, Carly Heitlinger and Ivania Caprio.

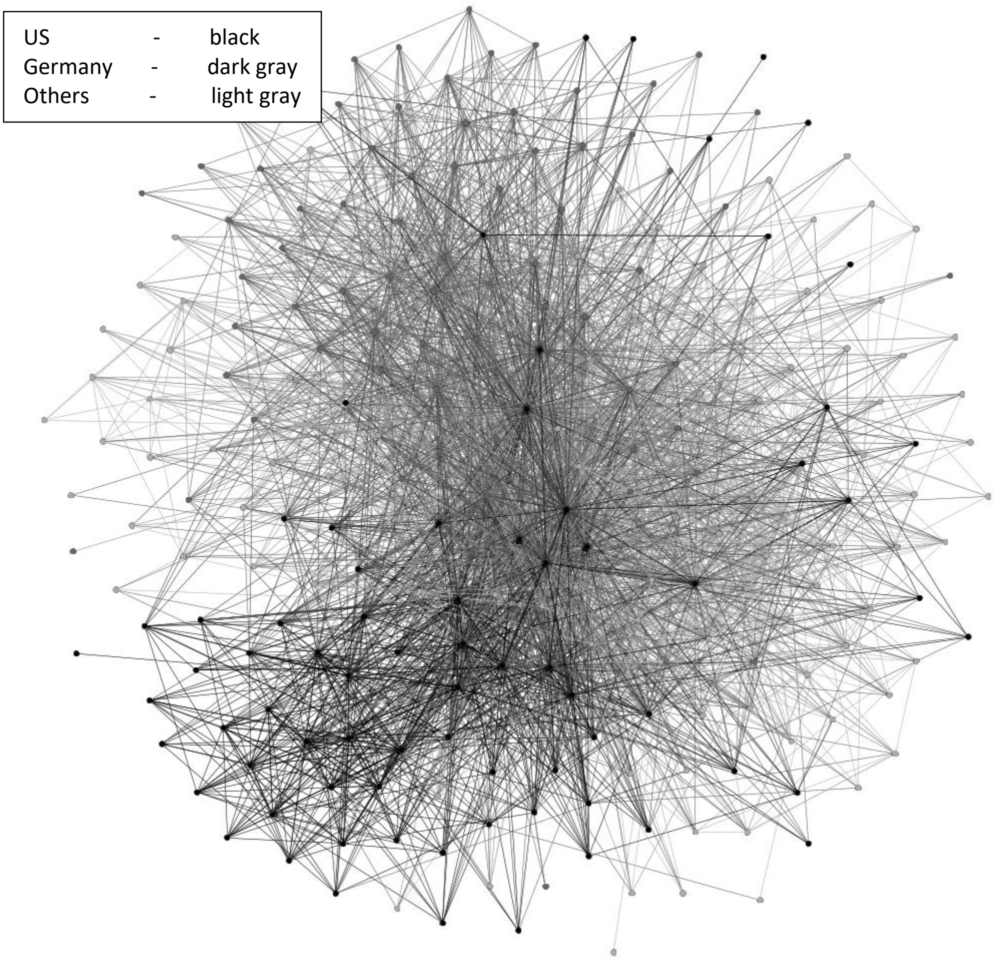


Figure 3: Influencer Network – Origin-based Coloring
Source: Own figure

The nodes / influencers in the network and the corresponding linkages / followings are color coded with influencers stemming from the US being black, those from Germany being dark gray and all others being light gray.

Figure 3 shows that while a distinct black and dark gray cluster exist, there are a number of ties between differently colored nodes. This gives rise to the second research whether in the context of Instagram influencing nationality plays a role when following another influencer.

Following the comment at the beginning of this section that only four influencers from the sample are absent from the network, the figure additionally shows that there also are only very few influencers with only one or two links to the network.

In total there are only five influencers in the data set with an out-degree of zero – excluding the four that are not part of the network, this leave only one in the network who does not follow any of the other 254 influencers. Excluding these five influencers, the average out-degree is 14.528 with a median of 13. The in-degree perspective, however, looks quite different and considerably more concentrated, with only 111 influencers having an in-degree of more than zero. The average in-degree of those that are different from zero is 32.7207 with a median of 22. This shows that even in this set of top influencers the major focus is concentrated on only a select few which in the previous section were termed α-influencers. It also shows that α-influencers are actually well-known to their peers and relevant to them as well.

Table 3: Best connected Influencers worldwide (by degree-centrality)

Name	Origin	In-Degree	Out-Degree	Degree Centrality
Ohhcuture (Leonie Hanne)	Germany	144	40	184
Songofstyle (Aimee Song)	USA	128	27	155
Chiaraferragni (Chiara Ferragni)	Italy	130	24	154
Weworewhat (Danielle Bernstein)	USA	80	58	138
Gighadid (Gigi Hadid)	USA	130	1	131
Milenasecret (Milena Karl)	Germany	62	38	100
Camilacoelho (Camila Coelho)	Portugal	77	15	92
Peaceloveshea (Shea Marie)	USA	67	23	90
Garypeppergirl (Nicole Warne)	Australia	74	11	85
Angelicablick (Angelica Blick)	Sweden	69	16	85

Source: Own table

Table 4: Most followed Influencers worldwide

Name	Origin	In-Degree
Ohhcuture (Leonie Hanne)	Germany	144
Gigihadid (Gigi Hadid)	USA	130
Chiaraferragni (Chiara Ferragni)	Italy	130
Songofstyle (Aimee Song)	USA	128
Taylor_hill (Taylor Hill)	USA	80
Weworewhat (Danielle Bernstein)	USA	80
Oliviapalermo (Olivia Palermo)	USA	79
Camilacoelho (Camila Coelho)	Portugal	77
Angelcandices (Candice Swanepol)	South Africa	75
Garypeppergirl (Nicole Warne)	Australia	74

Source: Own table

Considering that 111 of 255 (43.53%) report an in-degree of more than one shows that the sampling of influencers introduced in section 3.1 is suitable. A significant share of the sampled influencers is considered relevant even among their peers.

Table 3 and *Table 4* summarize the best-connected actors by considering the overall degree centrality as in-degree plus out-degree and the most followed influencers measured via the in-degree. While some influencers appear in both tables, the match is not perfect. This is witnessed as well from a Spearman rank correlation coefficient of 0.774 between the in-degree and the degree centrality. The presence of a number of Germans among the top of these lists validates as well their strong presence in the overall data set.

From a practical point of view, this means that while a strong relation exists between the well-connected actors in a network and those that are followed strongly by others, this link is not perfect. Thus, an importance indicator that is built upon the overall structure of the network will provide additional important insights, while a view based solely on follower numbers cannot.

Building on the introduction to Social Network Analysis in section 3.2 the eigenvalue centrality and the betweenness centrality as measures or approximations of an influencer's importance and reach have been calculated. With all influencers plotted into a diagram for the Importance and Reach scores, *Figure* 4 results.

Compared to the diagrams in *Figure* 1 and *Figure* 2 it is no longer possible to make out particular clusters, but different layers can be conceived. Calculating Spearman correlation coefficients (both indicators are strongly non-normal) reveals that there is a strong correlation of r = 0.940 (p = 0.000) between the two variables. However, most of this relation stems from the fact that more than 150 influencers report a score of 0 in both indicators. The correlation drops to r = 0.543 (p = 0.000) if these cases are excluded. Nevertheless, in either of the two cases a Cronbach's α of 0.085 or 0.082 respectively (excluding the zero cases) reveals that both variables describe significantly different concepts.

Considering the depiction of the two indicators as in *Figure* 4, the outer layer consists of Danielle Bernstein, Leonie Hanne, Chiara Ferragni, Aimee Song and Gigi Hadid, whereas the second layer would be Nicolle Ciotti, Milena Karl, Nicole Warne, Candice Swanepoel and Taylor Hill.

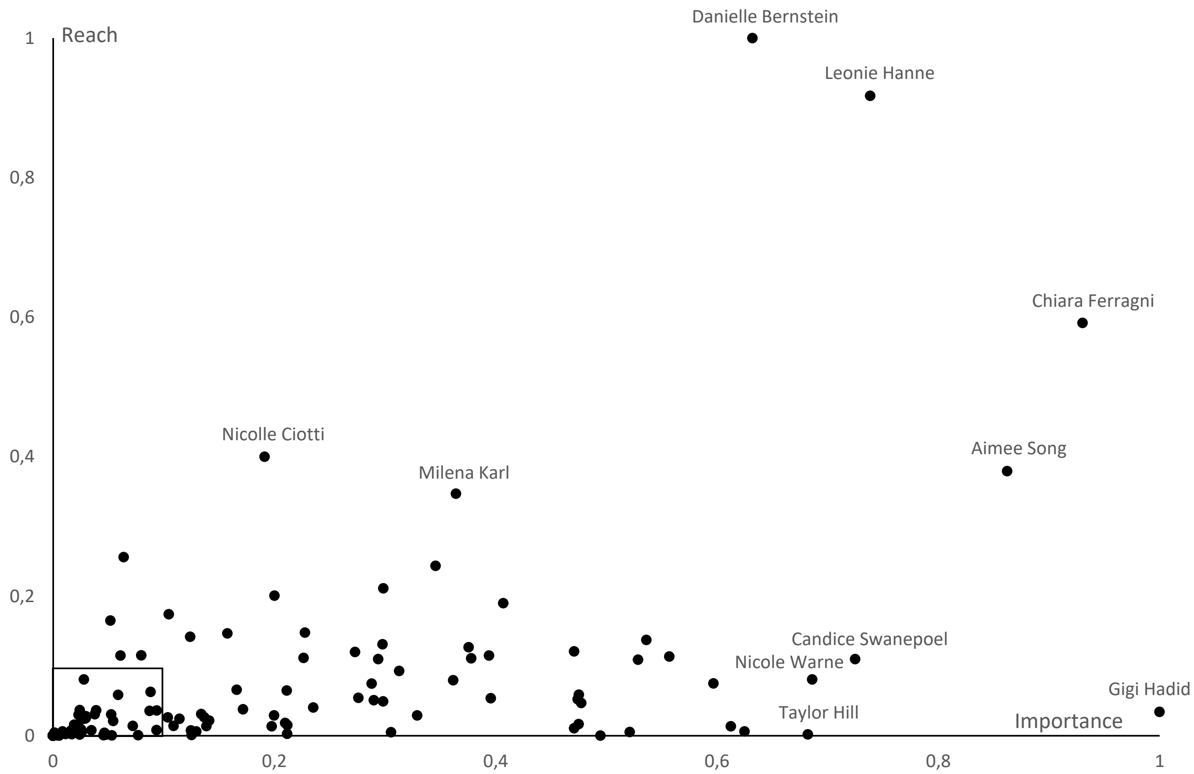


Figure 4: *Influencers' Importance and Reach*
Source: *Own figure*

This again motivates the idea of α-influencers. The box in the lower left is bounded by an Importance and Reach score of 0.1, and similar to the box in *Figure* 1 captures roughly 80% of all influencers with the majority of them (154 in total) being situated at a score of zero – which is achieved instantaneously if the in- or out-degree is zero.

A differentiation into α-, β- and γ-influencers might thus be a helpful classification. The box in the lower left then contains γ-influencers. The gammas play almost no role at all in the network, while, however, still being a part of it. The β-influencers are somewhat relevant in the network and would be all those not explicitly mentioned by name. Finally, the α-influencers are clearly dominating not only in regard to their followers in general, but as well in regard to their peers. While the distinction of actors in a network into particular roles in considered in some studies on Social Media like Havakhor et al. (2016) in the context of influencers and in particular fashion influencers, no such study exists at this point.

4.3 International Links between Influencers vs. National Clusters

Since Figure 3 already illustrates the international relations of the influencers, in this section the focus lies on determining the magnitude of these relations.

Table 5 together with an average number of links of 28.94 more or less implies that except for the US and Germany, influencers with a different origin need to integrate internationally to become a relevant player in the network.

Table 5: Top 5/6 most followed Influencers in Germany and in the US

Germany			USA		
Name	In-Degree National	In-Degree International	Name	In-Degree National	In-Degree International
Stefaniegiesinger (Stefanie Giesinger)	54	65	Songofstyle (Aimee Song)	45	128
Ohhcuture (Leonie Hanne)	46	144	Somethingnavy (Ariell Noa Charnas)	40	67
Novalanalove (Farina Opoku)	41	54	Thriftandthreads (Brittany Xavier)	37	62
Pamela_rf (Pamela Reif)	39	55	Gigihadid (Gigi Hadid)	36	130
Milenasecret (Milena Karl)	37	62	Blankitinerary (Paola Alberdi)	33	58
Matiamubysofia (Sofia Tsakiridou)	37	53			

Source: Own table

Focusing thus on the US and Germany in particular, Table 5 summarizes the number of followers the top-influencers have that share the same origin vs. how many followers they have in total among their peers worldwide.

While it is not incidental that many of the reported names coincide with the names already mentioned in the previous section in the discussion of *Figure* 4. It is interesting to note that for all of them there is a discrepancy between the international in-degree, being in three cases almost up to three times as high as the national one. This clearly strengthens the impression already obvious from *Figure* 3 that significant international linkages exist between the top influencers.

Combining the results with those from *Figure* 4, however, seems to indicate that the degree of international activity is not strongly linked to an influencer's position, her relevance in the network of her peers. Influencers can thus become important players locally as well as globally - positions that in Social Network Analysis are called local and hidden champions.

If this analysis is expanded to encompass the whole dataset and the overall number of links between influencers Table 6 results. The first entry in each cell marks the absolute number of links between influencers of the respective country combination. Considering that the sample contains differing numbers of influencers for each of the three origins, the numbers were adjusted by division with the number of influencers of each of the two countries (For illustrative purposes the results are multiplied by a factor of 100 afterwards). Before adjustment, a Cramer's V of 0.3246 results and afterwards of V = 0.3397. In either case, indicating a strong relation and thus a pronounced structure contained within the dataset.

Table 6: Links between influencers of different origins

		Influencer from…		
		USA	Germany	Rest of World
follows influencer from	USA	665 11,2161	149 2,7644	291 3,4993
	Germany	250 4,6382	649 13,2449	319 4,2196
	Rest of World	413 4,9663	257 3,3995	639 5,4784

Source: own table

While influencers from the rest of the world are mostly independent of their choice of whom to follow – which might also be due to the fact that it encompasses a number of countries – for the USA and Germany a distinct home-bias can be observed. Nevertheless, for the USA about half of the links go abroad, while for Germany it is almost 40%. This clearly indicates that links between influencers are not bound by national borders. However, if the numbers in Table 6 are compared to those in Table 5 it can also be seen that it is mainly the top influencers previously termed α influencers that drive the process.

Going back to section 3.1 and the sample of influencers used in the course of this study. It has been criticized that the list of selected influencers favors the US and Western Europe, excluding significant parts of Asia, the Middle East, South America and Africa. While the sample originates from lists of internationally relevant influencers, it is prudent to assume that a significant share of locally very successful influencers might have been left out of the sample. Thus, the 80-20 rule might hold in this context as well, assuming that this study only focuses on the globally well-known influencers and thereby excludes 80% of influencers that only matter as local champions. Incorporating local champions as well however would require a comparative in-depth analysis of a number of local Social Media spheres and will not be part of this study. Considering Twitter, Bakshy et al. (2011) provides evidence that leads to suspect that a share of 80% of influencers that only enjoy local relevance might indeed be a phenomenon across multiple Social Media platforms. In either case, the bias would only shift the focus of this study from influencers in general to the major influencers of international renown.

While the insight that top influencers are internationally linked might not be big news to anyone active in Social Media Marketing, this study shows it quantitatively and measure its extent on a comprehensive if not fully exhaustive basis for the women's fashion sector, a significant sector in Social Media influencing.

5 Conclusions, Limitations and Outlook

5.1 Summary

In the present study, data for 255 influencers from the field of women's fashion has been considered to gain new insights for quantitative influencer marketing on Instagram. Additionally, the network among the sampled influencers has been used to generate new indicators that can be implemented to determine the relevance or importance of influencers not solely in regard to their followers but in particular in regard to their peers. While this idea in itself is not new (Havakhor et al., 2016) this study provides to the discussion in two ways.

The first research question considers how a network-inherent ranking of influencers (section 4.2) as compared to one based on an exogenously given rating scheme can be developed. Aside from Havakhor et al. (2016) (e.g. betweenness centrality) who also implemented some network-inherent indicators other studies use evaluations of influencers that result from exogenously defined importance measures (Aggrawal et al., 2018; Arora et al., 2019; Mittal et al., 2020). Second, due to severe restrictions in the Instagram API current studies focus mostly on Twitter (Arora et al., 2019; Bakshy et al., 2011; Cha et al., 2010; Mittal et al., 2020; Weng et al., 2010), YouTube (Aggrawal et al., 2018) or Facebook (Arora et al., 2019; Cavalli et al., 2011) and Instagram as a Social Media platform with its peculiarities remains severely under researched except as part of the study by Arora et al. (2019). Third, many of the studies focus on the functionality of their approaches and marketing or sectoral points of interest are considered secondary at best. In contrast, this study implemented a well-constructed sample to offer insights into the field of women's fashion (section 4.1).

Based on the extracted network eigenvalue and betweenness centrality, two orthogonal measures, are introduced and shown to contribute to the description of an influencer's importance and reach (second part of section 4.2). Using the distribution of the influencers in accordance to these two indicators allows differentiating between α-, β- and γ-influencers (based on the statistics as summarized in *Figure* 4). A distinction that shows which influencers have a significant impact not only on their followers but on their peers as well, versus those that only matter with regard to their own followers. *Figure* 4 illustrates the distribution of influencers and makes that the α-influencers are far superior in both regards of importance and reach whereas the γ-influencers do not matter at all in the network of their peers. This result expands the study by Havakhor et al. (2016) and as well the one by Mittal et al.

(2020) who both argue that at least a combination of core metrics is required to determine an influencer's relevance. Bakshy et al. (2011) additionally stresses that in addition to the current relevance of followers, it is their past relevance that matters as well; an aspect that in this study is covered by the eigenvalue centrality since a well-established position in the network can only be the result of previous work and its acceptance by their peers.

The second research question asked about the links between influencers and whether the influencers based on their origins are nationally segregated or whether nationality does not play a relevant role. Building on the constructed network of following relations, the extent of nationality-based clustering has been studied. It has been shown that while a bias to link to influencers from the same country of origin – more pronounced in Germany than in the US – is present as witnessed by a Cramer's V of 0.3397 there still exist a significant number of international links that allow to argue that in particular the top influencers (as in α and β influencers) are globally well integrated.

These insights complement the arguments by Lengyel et al. (2015) and Han et al. (2018) that the death of distance hypothesis potentially holds for Social Media platforms in general or Instagram in particular, but surely does so for the sub-group of top influencers in this particular field of study.

The study thus provides additional inputs for marketing practitioners active in the field of Social Media marketing that are looking for additional inputs or suitable metrics to evaluate the relevance of the influencers or affiliates they cooperate with.

5.2 Conclusions for Practitioners

While there already exists software packages that focus on quantitative aspects of influencer marketing, these packages regularly only focus on the performance of one particular influencer evaluated against a previously determined set of metrics. The focus on only a single influencer, usually the one being managed by the user of the respective software solution, is due to continuous changes to Instagram's API that increasingly preclude the automatic access to most data except for a personal account – similar argument although on a lesser scale hold for other Social Media platforms as well. Platforms that offer cross-sectional data on influencers like Phlanx are limited in their scope on a report of core metrics.

While the logic behind using the core metrics implemented in most software solutions still in existence cannot be criticized this type of approach offers only absolute metrics and thus an absolute frame of reference. A relative perspective, however, is at least of equal importance. This study has shown that using a relative approach to influencer marketing allows for a much more multi-facetted perspective and it allows for a quantification of the previously rather qualitative measures of importance and reach. Thus, using the proposed procedure and the deduced modes of analysis detailed in the context of the first research question, a comparative study and thus a comparative evaluation of influencers is possible and can add an important quantitative dimension to the evaluation of an influencer's value.

Additionally, the two measures do not require an exogenously determined scoring model but provide information on the influencers based on their position in the network of their peers alone.

The present study delivers a first evaluation of the most relevant influencers in the field of women's fashion to be used by practitioners from this field. It also offers a first quantitative analysis indicating that importance and reach not necessarily coincide but offer two distinctly different points of view, even if approximated by eigenvalue and betweenness centrality. Thus, the study motivates to differentiate influencers (which at this point implies top influencers) into two or potentially three groups – α-, β- and γ-influencers. Cooperation with an α-influencer will add the bonus that the influencer's posts not only reach her direct followers, but might generate compound multiplier effects by influencing other influencers as well. This compound effect of top-level influencers could additionally be used as a measure of an influencer's value.

Thus, the results of this study provide valuable insights for companies as well as for influencers themselves. Companies trying to evaluate influencers they are planning to cooperate with have a multifacetted tool to identify sets of suitable partners while influencers can evaluate their own worth, their potential rivals and establish a better, more scientifically founded bargaining position.

Considering that the death-of-distance hypothesis holds for in particular for α-influencers adds to the practical relevance of the arguments given above since α-influencers not only have a multiplying effect by influencing other influencers, they also reach a more international audience. Thus, applying the indicators introduced herein will give a company a perspective on areas that will be particularly impacted by this multiplier effect. It will thus alleviate the selection process of the right influencer for a particular campaign.

5.3 Limitations and Outlook

This study is limited to the data present for a single year. In this regard, it has not been possible to study dynamics influencing the network constructed herein. It was thus not possible to ascertain that the results of the study hold over time.

Additionally, the field of women's fashion has been selected because it already is a developed field with a number of actors that allow for a broader analysis. Working with a network that can be considered fully developed has the problem that the development path that lead to the situation as captured in this study can no longer be studied in more detail. Aside from expanding the regional perspective of this study or its focus, the question can furthermore be raised whether the results can be extended to other sectors or Social Media platforms.

The study focused on a sample of globally active and well-known influencers and can be considered as suitably representative. Nonetheless, a number of locally relevant influencers from South East Asia, Africa, the Middle East and in part Southern America might have been excluded as they do not appeal to a global audience. While this does not impact the validity of the findings in this study, it might provide additional research incentives and raises the question of what makes a locally relevant influencer become globally relevant.

An additional question of particular interest is whether and to which extent the international links in the network form at the beginning of an influencer's career, or whether established influencers when they enter a new medium first develop a national followership or transfer their previously active followership from an old medium into the new one. In a similar direction, the question can be raised whether the development path of an influencer and their integration into the network of peers is different if they enter Instagram as their first and primary medium or when they already established themselves on a different platform.

In the analytical part, it has already been established that some core metrics of an Instagram influencer are correlated while others clearly are not. The question can thus be asked whether building on the core metrics and the resulting network of peers, a comprehensive model explaining the importance of an influencer can be constructed.

Appendix

Table 7: List of Sampled Influencers

_thefab3	courtney_shields	janicejoostema	mariapombo	sarah.harrison.official
by.iris.sophia	cribuccino	janinapfau	marieserneholt	sassyredlipstick
annelaurenmais	darya	janinauhse	marinathemoss	sav.labrant
adriannasf	darylanndenner	jannid	martacarriedo	scarlettgartmann
alexachung	designdschungel	jeannedamas	martapozzan	seewantshop
alexis.belbel	desiperkins	jeennny____	maryanaro	serlinahohmann
aliciastylish	dianazurloewen	jordanunderwood	masha	shantijoantan
alwaysjudging	dominokati	josefinehj	mathildegoehler	si_sichen
alyson_haley	donnaromina	jourdansloane	matiamubysofia	sierrafurtado
amberfillerup	double3xposure	juelimery	mattssonmoa	sincerelyjules
anajohnson	dreachong	juleslw	mayastepper	sistinestallone
andreabelverf	dressupbuttercup	juliahengel	melinasophie	sivanayla
andreaviktoria	ebbazingmark	julialundinblog	melissackoh	sofiarichie
angelcandices	lyss	junesixtyfive	melissasatta	ariellecharnas
angelicablick	ele.rc	kateymcfarlan	michelletakeaim	songofstyle
anna.wilken	elenacarriere	katharinadamm_official	mikutas	sonyaesman
annamariadamm	eleonoracarisi	kathleen_barnes	milena.karl	sophiachong
annatatangeloofficial	ellabrooksblog	kbstyled	miss_gunner	sophieelkus
anniju__	elle_ferguson	kenzas	missalena.92	spanglishfashion
anuthida	emaxlouise	kimhnizdo	missysueblog	stefaniegiesinger
ashleyrobertson	emilyanngemma	kisu	mollyrustas	stuartbrazell
aspynovard	emilyvartanian	laurabeverlin	mvb	styledsnapshots
aylin_koenig	emitaz	lauraescanes	naomineo_	stylescrapbook
belenhostalet	emmaroseofficial	laureen	nastilove	susiebubble
belluspuera	esmirnatapia	Laurenelizabeth	natasupernova	tammyhembrow
bettyautier	estefaniac2t	laurenkaysims	nhitastic	tatjanamariposa
bettytaube	euniceannabel	lenagercke	nicholeciotti	taylor_hill
biancabrandolini	fannylyckman	lenaperminova	nicolefalciani	teresaandresgonzalvo
biancaingrosso	fashiioncarpet	lenaterlutter	nicolettemason	thassianaves
black_palms	fashion_jackson	leomieanderson	ninalaureen	thebeautybeau
blaireadiebee	fashionedchicstyling	limaswardrobe	ninasuess	thefashionguitar
blankitinerary	fata.hasanovic	lindatol_	ninauc	themrsgibby
bonniestrange	fede_nargi	linnahlborg	kayla_seah	brittanyxavier
camilacoelho	gabifresh	lisa.olssons	novalanalove	tonigarrn
camillecharriere	galagonzalez	lisadengler	leoniehanne	tonyamichelle26
caraloren	nicolewarne	lisamarie_schiffner	oliviapalermo	trendy_taste
carina	gigihadid	lizkaeber	pamela_rf	valentinapahde
carlotaweberm	gypsea_lust	lolariostyle	pandorasykes	vallibeatrice
carly	hannalicious	lornaluxe	patriziapalme	vanessafuchs
carmushka	hauteofftherack	love_aesthetics	pau_eche	vickyheiler
caro_e_	helenowen	alexandrapereira	sheamarie	victoriatornegren
carodaur	christineandrew	luanna	pernilleteisbaek	vivaluxuryblog
celinebethmann	howimetmyoutfit	lucywilliams02	phiaka	walkinwonderland
champagneandchanel	iluvsarahii	luisalion	ploychava	wendyslookbook
charlottebridgeman	imjennim	lydia.webb	queenofjetlags	wethepeoplestyle
chiarabiasi	ischtarisik	lydiamillen	rachparcell	weworewhat
chiaraferragni	itscaroo	majawyh	rocky_barnes	xenia
chrisellelim	itziaraguilera	marenwolf	rosielondoner	xeniaadonts
claudiaalende	ivanikolina	jennycipoletti	rozalia_russian	xlaeta
cmcoving	jaceyduprie	mariafrubies	salinachai	yvonnepferrer
collagevintage	jaglever	mariakragmann	sannealexandra	zorannah

Source: Own table

References

Aggrawal, N., Arora, A., Anand, A., & Irshad, M. S. (2018). View-count Based Modeling for YouTube Videos and Weighted Criteria-based Ranking. In M. Ram & J. P. Davim (Eds.), *Advanced Mathematical Techniques in Engineering Sciences* (pp. 149–160). CRC Press.

Argyris, Y. A., Wang, Z., Kim, Y., & Yin, Z. (2020). The effects of visual congruence on increasing consumers' brand engagement: An empirical investigation of influencer marketing on instagram using deep-learning algorithms for automatic image classification. *Computers in Human Behavior*, *112.* https://doi.org/10.1016/j.chb.2020.106443

Arora, A., Bansal, S., Kandpal, C., Aswani, R., & Dwivedi, Y. (2019). Measuring social media influencer index- insights from facebook, Twitter and Instagram. *Journal of Retailing and Consumer Services*, *49*, 86–101.

Aswani, R., Kar, A. K., & Chandra, S. (2017). Identifying Buzz in Social Media: A Hybrid Approach Using Aritificial Bee Colony and k-nearest Neighbors for Outlier Detection. *Social Network Analysis and Mining*, *7*(1), 38. https://doi.org/10.1007/s13278-017-0461-2

Audrezet, A., Kerviler, G. de, & Guidry Moulard, J. (2018). Authenticity under Threat when Social Media Influencers need to go beyond Passion. *Journal of Business Research.* Advance online publication. https://doi.org/10.1016/j.jbusres.2018.07.008

Bakshy, E., Hofman, J. M., Mason, W. A., & Watts, D. J. (2011). Everyone's an influencer. In Association for Computing Machinery (Ed.), *Proceedings of the Fourth ACM International Conference on Web Search and Data Mining* (pp. 65–74). Association for Computing Machinery. https://doi.org/10.1145/1935826.1935845

Bendoni, W. K. (2017). *Social media for fashion marketing: Storytelling in a digital world*. Bloomsbury Visual Arts.

Block, E. (2016). *35 Top Fashion Influencers for When You're in Need of Fresh Inspo*. http://www.whowhatwear.co.uk/best-fashion-influencers/slide1

Boyd, D. M., & Ellison, N. B. (2007). Social Network Sites: Defition, History, and Scholarship. *Journal of Computer-Mediated Communication*, *13*(1), 210–230.

Brown, D., & Hayes, N. (2008). *Influencer Marketing - Who Really Influences Your Customers*. Elsevier.

Cavalli, N., Costa, E., Ferri, P., Mangiatordi, A., Micheli, M., Pozzali, A., Scenini, F., & Serenelli, F. (2011). *Facebook Influence on University Students' Media Habits: Qualitative Results from a Field Research.* Media in Transition - Unstable Platforms: the Promise and Peril of Transition. https://boa.unimib.it/retrieve/handle/10281/23493/30093/MangiatordiMicheliScenini_Facebook_influence_on_university_students.pdf

Cha, M., Haddadi, H., Benevenuto, F., & Gummad, K. P. (2010). *Measuring User Influence of Twitter: The Million Follower Fallacy*. Washington, DC.

Collsen, L.-S. (2016). *South African Influencers you should know*. http://theculturetrip.com/africa/south-africa/7-south-african-fashion-bloggers/

De, S. S., Dehuri, S., & Cho, S.-B. (2020). Research contributions published on betweenness centrality algorithm: modelling to analysis in the context of social networking. *International Journal of Social Network Mining*, *3*(1), 1–34.

Editorial Staff. (2016). *Top Fashion Influencers on Instagram*. https://neoreach.com/top-20-fashion-influencers-instagram/

eMarketer. (2020). *Instagram Users and Growth in North America*. https://www.emarketer.com/chart/229518/instagram-users-growth-north-america-2018-2023-millions-change

Ferrari, A. (2018). *Top Fashion Influencers*. http://www.topfashioninfluencers.com

Fletcher, J. M., & Wennekers, T. (2017). From Structure to Activity: Using Centrality Measures to Predict Neuronal Activity. *International Journal of Neural Systems*, *28*(02). https://doi.org/10.1142/S0129065717500137

Forbes. (2018). *Top Influencers Fashion*. https://www.forbes.com/top-influencers/fashion/#67040574552c

Freeman, L. (1977). A Set of Measures of Centrality based on Betweenness. *Sociometry*, *40*(1), 35–41.

Gushcloud Pte Ltd. (2017). *Influence Asia*. https://influence-asia.com/full-list-of-nominees

Haenlein, M., Anadol, E., Farnsworth, T., Hugo, H., Hunichen, J., & Welte, D. (2020). Navigating the New Era of Influencer Marketing: How to be Successful on Instagram, TikTok, & Co. *California Management Review*, *63*(1), 5–25.

Hall, S. (2017). *Innovative B2B Marketing - New Models, Processes and Theory*. Kogan Page.

Han, S. Y., Tsou, M.-H., & Clarke, K. C. (2018). Revisiting the Death of Geography in the Era of Big Data: The Friction of Distance in Cyberspace and Real Space. *International Journal of Digital Earth*, *11*(5), 451–469.

Havakhor, T., Soror, A. A., & Sabherwal, R. (2016). Diffusion of Knowledge in Social Media Networks: Effects of Reputation Mechanisms and Distribution of Knowledge Roles. *Information Systems Journal*, *28*(1), 104–141.

Instagram. (2018). *About Us*. https://www.instagram.com/about/us/

Jin, S. V., Muqaddam, A., & Ryu, E. (2019). Instafamous and social media influencer marketing. *Marketing Intelligence & Planning*, *37*(5), 567–579.

Jin, S. V., Ryu, E., & Muqaddam, A. (2021). I trust what she's #endorsing on Instagram: moderating effects of parasocial interaction and social presence in fashion influencer marketing. *Journal of Fashion Marketing and Management.* Advance online publication. https://doi.org/10.1108/JFMM-04-2020-0059

Kim, S., Han, J., Yoo, S., & Gerla, M. (2017). How are Social Influencers Connected in Instagram? In G. L. Ciampaglia, A. Mashhadi, & T. Yasseri (Eds.), *Social Informatics* (pp. 257–264). Springer.

Klein, A. V. (2016). *18 Fashion Influencers to Watch in 2017*. https://fashionista.com/2016/12/fashion-social-media-influencers-to-watch-2017

Kozinets, R. V., Valck, K. de, Wojnicki, A. C., & Wilner, S. (2010). Networked Narratives: Understanding Word-of-Mouth Marketing in Online Communities. *Journal of Marketing*, *74*(2), 71–89.

Lagrée, P., Cappé, O., Cautis, B., & Maniu, S. (2018). Algorithms for Online Influencer Marketing. *ACM Transactions on Knowledge Discovery from Data*, *13*(1). https://doi.org/10.1145/3274670

Lammenett, E. (2017). *Praxiswissen Online-Marketing* (6.th ed.). Springer Gabler.

Lee, S., & Kim, E. (2020). Influencer marketing on Instagram: How sponsorship disclosure, influencer credibility, and brand credibility impact the effectiveness of Instagram promotional post. *Journal of Global Fashion Marketing*, *11*(3), 232–249.

Lengyel, B., Varga, A., Sagvari, B., Jakobi, A., & Kertesz, J. (2015). Geographies of an Online Social Network. *PloS One*, *10*(9), Article e0137248.

Lim, X. J., Rozaini, A., Cheah, J.-H., & Wong, M. W. (2017). The Impact of Social Media Influencers on Purchase Intention and the Mediation Effect of Customer Attitude. *Asien Journal of Business Research*, *7*(2), 19–36.

Lou, C., & Yuan, S. (2018). Influencer Marketing: How Message Value and Credibility Affect Consumer Trust of Branded Content on Social Media. *Journal of Interactive Advertising*, *19*(1), 58–73.

Mittal, D., Suthar, P., Patil, M., Pranaya, P., Rana, D. P., & Tidke, B. (2020). Social Network Influencer Rank Recommender Using Diverse Features from Topical Graph. *Procedia Computer Science*, *167*, 1861–1871.

Newman, M. (2018). *Networks* (2nd ed.). Oxford University Press.

Nirschl, M., & Steinberg, L. (2018). *Einstieg in das Influencer Marketing*. Springer.

Perret, J. K. (2021). The Social Brain of Social Media – A Physiological Boundary to the Number of Online Relations. *Forthcoming*.

Piper, J. (2019). *38th Semi-Annual Taking Stock with Teens Survey*. http://www.pipersandler.com/private/pdf/TSWT_Fall_2019_Infographic_11x17.pdf

Veirman, M. de, Cauberghe, V., & Hudders, L. (2017). Marketing Through Instagram Influencers: The Impact of Number of Followers and Product Divergence on Brand Attitude. *International Journal of Advertising*, *36*(5), 798–828.

Veirman, M. de, & Hudders, L. (2020). Disclosing Sponsored Instagram Posts. The Role of Material Connection with the Brand and Message-sidedness when Disclosing Covert Advertising. *International Journal of Advertising*, *39*(1), 94–130.

Weng, J., Lim, E. P., Jiang, J., & He, Q. (2010). Twitterrank: Finding Topic-Sensitive Influential Twitterers. *WSDM '10: Proceedings of the Third ACM International Conference on Web Search and Data Mining*, 261–270.

West, M. (2017). *50 Up and Coming Fashion Influencers in the USA*. https://blog.scrunch.com/fashion-influencers.usa

Wu, Q., Qi, X., Fuller, E., & Zhang, C.-Q. (2013). "Follow the Leader": A Centrality Guided Clustering and Its Application to Social Network Analysis. *The Scientific World Journal.* Advance online publication. https://doi.org/10.1155/2013/368568

Authors

Ms. Ronja **Edler**, M. Sc. finished her studies in Global Brand and Fashion Management at the International School of Management in Cologne in 2018 and in International Management at the Steinbeis-Hochschule-Berlin in 2020. She is currently employed by a major German telecommunications service provider. Her research interests include, in particular, brand management (social media marketing).

Prof. Dr. Jens K. **Perret** studied Business Mathematics and Business Administration at the University of Wuppertal. He finished his doctoral thesis in Economics on the knowledge society in Russia at the University of Wuppertal. Between 2004 and 2016 Mr. Perret worked at the European Institute for International Economic Relations first as a research assistant and later as a scientific researcher. From 2007 till 2016 Mr. Perret has been working as a Research Assistant at the Chair for Macroeconomic Theory and Policy. From 2012 to 2014 he has been a contractual lecturer at the Technical University Kaliningrad. Since September 2016 he holds a full professorship for Economics and Statistics at the International School of Management in Cologne.

Seibel, Kevin; Bingemer, Stephan; Brandt, Jens

Wahrgenommenes Datenzugriffsrisiko im Kontext von Big Data

Auswirkungen und moderierende Effekte auf das Konsumentenvertrauen deutscher Onlinekäufer

Received 26.01.2021 · Received in revision 23.06.2021 · Accepted 02.09.2021 · Available online

Abstract

Big Data und Datenschutz sind aktuell vieldiskutierte Begriffe mit hoher Relevanz für Marketing und E-Commerce. Negative Effekte der Kundendatensammlung und -verwendung sind jedoch bisher kaum erforscht. Die vorliegende Studie geht der Frage nach, wie sich das wahrgenommene Datenzugriffsrisiko, das durch Nutzung von Big Data entsteht, sowie die Ehrlichkeit eines Unternehmens auf das Konsumentenvertrauen deutscher Onlinekäufer und darüber hinaus auf deren Kundenbindung auswirken. Zusätzlich werden zwei moderierende Variablen (Alter und die subjektive Wichtigkeit von Datenschutz) innerhalb dieser Beziehung betrachtet. Hierzu wurden exemplarisch 128 Amazon-Kunden im Rahmen einer standardisierten Online-Umfrage untersucht. Die Ergebnisse der Studie bestätigen die alltägliche Erfahrung, dass Nutzer von digitalen Handelsangeboten, wie beispielsweise dem von Amazon, eine hohe Kundenbindung aufweisen. Dies ist der Fall obwohl aufgrund der inzwischen hergestellten Transparenz bekannt ist, dass in einem erheblichen Maße auf die Nutzerdaten zugegriffen wird, das wahrgenommene Datenzugriffsrisiko also hoch ist. Entscheidend sind somit das Vertrauen in den Anbieter sowie dessen Ehrlichkeit. Big Data bringt neben den Chancen für das Kundenbindungsmanagement also auch Risiken für Kundenbeziehungen mit sich. Das wahrgenommene Datenzugriffsrisiko kann negative wirtschaftliche Folgen haben. Unternehmen müssen adäquaten Datenschutz daher aktiv in ihr Vertrauens- und Kundenbindungsmanagement integrieren. Dabei müssen entsprechende Maßnahmen nicht nur ältere Konsumenten, sondern auch die jüngere Generation ansprechen. Die vorliegende Arbeit zeigt jedoch auch, dass der behandelte Themenkomplex noch weiterer Forschung bedarf, die sich näher mit Konsumentenvertrauen allgemein und den Auswirkungen von Big Data beschäftigt.

Keywords:

Big Data, Datenschutz, Datenzugriffsrisiko, Konsumentenvertrauen

1 Einleitung

Ein funktionierendes Kundenbindungsmanagement ist für Unternehmen angesichts eines global intensivierten Wettbewerbs und fortschreitender Digitalisierung hochrelevant, um sich in der Wahrnehmung der Kunden vom Wettbewerb differenzieren zu können. Auch die Forschung setzt sich verstärkt mit dem Thema auseinander (Homburg und Bruhn 2017). Gerade im Marketing ist die Nutzung von Big Data ein zentrales Thema (Martin et al. 2017) und Investitionen in Big Data Analytics steigen deutlich an (Müller et al. 2018).

Optimierte Kundenbeziehungen werden immer mehr zum Wettbewerbsvorteil (Bruhn 2018). Vertrauensmanagement ist dabei als zentraler Teil des Customer Relationship Managements (CRM) sowohl für die Forschung als auch für Unternehmen wichtig und sollte fest in die Unternehmensstrategie integriert sein (Brickau und Städter 2011). Das Kundenvertrauensmanagement im Handel sieht sich durch die Digitalisierung jedoch mit neuen Herausforderungen konfrontiert (Bitkom 2017). Unternehmen verlassen sich immer mehr auf Empfehlungen, die auf Basis von Big Data gewonnen werden. Dabei sind sie sich vertrauenskritischen Situationen, die durch die Verletzung der Privatsphäre im Rahmen der Verwendung von personenbezogenen Daten entstehen können, kaum bewusst. Gemessen an seiner Relevanz, ist dieses Themenfeld wissenschaftlich nur unzureichend erforscht (Martin et al. 2017).

Insbesondere der elektronische Handel wird durch seinen Datenreichtum zunehmend Gegenstand privatsphärebezogener Untersuchungen (Wedel und Kannan 2016). Die Konsumentenpsychologie beschreibt einen Paradigmenwechsel durch das Internet und spricht vom „Konsument 2.0“ (Stephan und Werther 2013, S. 125). Dieser sucht aktiver nach Informationen und setzt sich mit der Sammlung der eigenen Daten durch Unternehmen auseinander (Stephan und Werther 2013). Deutsche sind dabei besonders risikoavers und kritisch im Umgang mit personenbezogenen Daten (Clemons et al. 2016; Morey et al. 2015). Gleichzeitig ist ihnen laut der Studie von Morey et al. (2015) kaum bewusst, welche Daten sie bewusst oder unbewusst online teilen. Aktuell verschärft sich die Haltung gegenüber Big Data jedoch international. Das Thema Datenschutz ist spätestens mit der Datenschutz-Grundverordnung (DSGVO) und der E-Privacy-Verordnung sowie beispielsweise dem Datenskandal von Facebook und Cambridge Analytica hochrelevant für die Wirtschaft geworden (Puscher 2018; Gondorf 2018). Eine Studie des Marktforschungsunternehmens Innofact zum Facebook-Skandal zeigte beispielsweise, dass jeder dritte Nutzer nun seine Aktivitäten einschränken oder gar sein Profil löschen will (Bialek 2018). Waren Unternehmen 2016 trotz intensiver Kundendatennutzung noch unzureichend auf die DSGVO vorbereitet (Bitkom 2016), drohen nach Inkrafttreten hohe Strafen bei unsachgemäßer Datensammlung und -verwendung (Das Europäische Parlament und Der Rat der Europäischen Union 2018a; Der Bundestag und Der Bundesrat 2018).

Doch Big Data birgt nicht nur regulatorische Sanktionsrisiken. Auch auf Konsumentenseite können negative Effekte entstehen. Alleine das Wissen über den Besitz und die Verarbeitung von personenbezogenen Daten durch Unternehmen kann negativ beim Kunden wirken und das Vertrauen schädigen (Martin et al. 2017).

Dabei ist fraglich, ob Internetnutzer die Datensammlung tatsächlich als kritisch wahrnehmen und Big Data in der Folge negative Effekte auf den ökonomischen Erfolg eines Unternehmens haben kann. So sind beispielsweise Gewinne und Userzahlen von Facebook trotz des Datenskandals weiter gestiegen (Deutscher Marketing Verband e.V. 2018), obwohl Facebook-Nutzer – wie bereits angemerkt – ihre Aktivitäten einschränken wollten (Bialek 2018). Gerade im Onlineumfeld bietet sich viel Forschungspotenzial bezüglich Vertrauen, Kaufverhalten und relevanten Moderatoren auf die Wirkzusammenhänge (Gefen et al. 2008).

2 Theorie und Forschungsstand

Das Kundenbindungsmanagement stellt den disziplinären Rahmen innerhalb der BWL dar, in dem das Konsumentenvertrauen theoretisch verankert ist. Der englische Begriff CRM bezieht sich genau genommen auf „den informationstechnischen Rahmen" (Homburg und Bruhn 2017, S. 7) des Kundenbeziehungsmanagements, beschäftigt sich letztlich aber auch mit der Kundenbindung (Homburg und Bruhn 2017) und wird nachfolgend synonym verwendet. Homburg und Bruhn (2017) identifizierten Vertrauen schon früh als Teil-Konstrukt des Multi-Level-Konstrukts Kundenloyalität, welches über das Konstrukt der Kundenbindung den wirtschaftlichen Erfolg eines Unternehmens treibt. Diese Wirkkette ist in der BWL gut untersucht und ist auch für das Online-Marketing gültig (Kollmann 2013).

Kundenbindung beinhaltet der gängigen Literatur nach die Dimensionen *Wiederkauf*, *Zusatzkauf* (Cross Buying) und *Weiterempfehlung*. Sie äußert sich sowohl in faktischem Verhalten als auch in Verhaltensabsichten (Nerdinger et al. 2015; Homburg und Bruhn 2017). Entsprechend kann Kundenbindung ex-post und ex-ante gemessen werden. Die ex-ante Messung erfasst psychologische Konstrukte wie Verhaltensintentionen, die als Indikator für zukünftiges Verhalten betrachtet werden (Nerdinger et al. 2015; Meyer und Oevermann 1995). Die Manifestation der Loyalität in Bindung erfolgt, wenn sich die reduzierte Wechselbereitschaft in tatsächlich treuem Verhalten (Wiederkauf, Zusatzkauf, Weiterempfehlung) niederschlägt (Homburg und Bruhn 2017). Diese Ausführungen unterstützt auch die wirtschaftspsychologische Literatur, die Kundenbindung vor allem aus einstellungsorientierter Nachfragerperspektive betrachtet (Nerdinger et al. 2015). Kundenbindung ist demnach ein psychisches Konstrukt (Gröppel-Klein et al. 2017; Fournier 1998), das innere Bindungszustände umfasst (Georgi 2010). Als psychologischer Faktor beeinflusst sie den Unternehmenserfolg und resultiert in ökonomischen Kennzahlen wie dem Customer Lifetime Value (CLV) (Homburg und Bruhn 2017; Bruhn 2016). Weiterhin werden neuere Konzeptualisierungen diskutiert, die zusätzlich die Preiserhöhungstoleranz als vierte Dimension der Kundenbindung (Homburg und Bruhn 2017) einbeziehen.

Die Ursachen für Bindung lassen sich der Lehre nach in fünf Kategorien aufteilen: situative, vertragliche, ökonomische, technisch-funktionale und psychologische (Meyer und Oevermann 1995), wobei letztere dominant ist (Gröppel-Klein et al. 2017). Kundenbindung beruht u.a. auf psychologischen Lernprozessen (Homburg und Stock-Homburg 2016) und kann auf freiwilliger oder unfreiwilliger Basis entstehen. Vertrauen zählt zu den wichtigen psychologischen Bindungsursachen (Grohmann et al. 2017) und lässt freiwillige Kundenbindung entstehen (Bruhn und Homburg 2017). Es beschreibt „das Gefühl eines Kunden, sich auf das zukünftige Verhalten eines Anbieters verlassen zu können“ (Nerdinger et al. 2015, S. 123). Vertrauen ist für den Aufbau von langfristigen Geschäftsbeziehungen essentiell (Sirdeshmukh et al. 2002) und stellt einen wichtigen Wettbewerbsvorteil dar (Ebert 2007). Es setzt voraus, dass der Kunde nicht nur geschäftlich sondern auch auf affektiver Ebene mit dem Anbieter zufrieden ist (Grohmann et al. 2017). Echte Kundenbindung, die sich im Konsumentenverhalten äußert, kann nur durch die Verbindung von kognitiver und affektiver Loyalität entstehen (Grohmann et al. 2017).

2.1 Vertrauen in Kundenbeziehungen

Bauer et al. (2006) haben Erkenntnisse der interdisziplinären Vertrauensforschung zusammengetragen und in den Kontext des Kundenbindungsmanagements gestellt. Marketingrelevante Themenkomplexe sind demnach beispielswiese die Rolle von Vertrauen als Heuristik (Gierl 2006) und kognitive Entlastung (Esch und Ruterberg 2006), bei Preisgünstigkeitsurteilen, Nachkaufdissonanzen (Müller-Hagedorn et al. 2006) und Preisstrategien (White und Yuan 2012). Vertrauen wirkt generell positiv auf ökonomische Beziehungen (Kenning und Blut 2006). Wirtschaftliche Vertrauensbeziehungen können in drei Kategorien unterteilt werden: Person-to-Person, Organisation-to-Organisation und Person-to-Organisation (Ebert 2007). Konsumentenvertrauen fällt der Literatur nach unter letztere Kategorie und stellt eine spezielle Form des Vertrauens in Kunde-Käufer-Beziehungen dar (Neumann 2007; Kenning und Blut 2006).

Das Konzept des Konsumentenvertrauens wurde im deutschsprachigen Raum durch Bauer et al. (2006) eingeführt und ausführlich als Konstrukt durch Neumann (2007) operationalisiert. Martin et al. (2017) stellen das Konsumentenvertrauen in direkten Zusammenhang mit unternehmerischer Datennutzung und Privatsphäre. Andere aktuelle Forschung begreift das Vertrauenskonstrukt hingegen entweder als zu eindimensional (z.B. Clemons et al. 2016) oder stellt es nicht in den Konsumentenkontext (z.B. Tasselli und Kilduff 2018; Vanhala und Ritala 2016; Kuipers 2018).

In der Literatur geht man aktuell davon aus, dass es sich beim Konsumentenvertrauen um ein spezifisches Vertrauen handelt, das auf der Wahrnehmung gewisser Unternehmenscharakteristika basiert und seine theoretische Fundierung u.a. in der psychologischen Lerntheorie – v.a. in der operanten Konditionierung (Gerrig und Zimbardo 2015) – hat. Konsumenten lernen innerhalb der Kundenbeziehung, ob sie einem Unternehmen vertrauen können (Neumann 2007). Neumann definiert es als „die Einstellung eines Konsumenten, dass ein Unternehmen die Fähigkeit besitzt, kompetent eine Leistung zu erbringen, ehrlich und offen am Markt auftritt und zudem seinen Kunden auch emotional verbunden ist“ (Neumann, 2007, S. 142).

Nach Neumann (2007) besteht Konsumentenvertrauen aus vier Dimensionen: *Ehrlichkeit*, *Kompetenz*, *Offenheit*, *emotionale Verbundenheit*. Laut Martin et al. (2017) spielen sowohl das rein *kognitive Vertrauen* (orig.: *Cognitive Trust*), d.h. „the customer’s willingness to rely on a firm in which (s)he has confidence“ (Martin et al. 2017, S. 39), als auch die potenzielle *emotionale Verletzung* (orig.: *Emotional Violation*) in der Kunde-Unternehmen-Daten-Beziehung eine Rolle. Während das kognitive Vertrauen also sinngemäß die ersten drei Dimensionen des Konsumentenvertrauens von Neumann (2007) einfängt, wird die emotionale Verbundenheit über die emotionale Verletzung in den Kontext von Datenwertschöpfung und Konsumentenvertrauen integriert.

Diese Operationalisierung umfasst – analog zum interpersonalen Vertrauen – neben einer kognitiven also auch eine affektive Komponente (vgl. McAllister 1995; Lewis und Weigert 1985). Zudem weisen Martin et al. (2017) signifikante Zusammenhänge ihrer Konstrukte mit Weiterempfehlungs-, Wechsel- sowie informationsverfälschenden Verhaltensabsichten von Konsumenten nach und integrieren somit auch einen konativen Aspekt. Das aktuelle Konsumentenvertrauen kann sich nicht auf bereits gezeigtes, zurückliegendes Konsumentenverhalten auswirken, weshalb eine Betrachtung der Verhaltensabsichten statt des tatsächlichen Verhaltens in diesem Kontext plausibel ist (Neumann 2007; Giering 2000; Martin et al. 2017).

Unter psychologischen Gesichtspunkten weist das Modell von Martin et al. und Kollegen (2017) geringe Mängel auf. Es folgt zwar der psychologischen Mehrheitsauffassung von Vertrauen als Einstellung (vgl. Petermann 2013) und enthält alle klassischen Einstellungskomponenten (vgl. Felser 2015). Das Modell ignoriert jedoch die persönlichkeitsbasierte Dispositionskomponente von Vertrauen (vgl. Rotter 1971). Dabei inkludiert es allerdings die sozialpsychologische Auffassung, dass Vertrauen aus Kognitionen über den Vertrauensgeber besteht (vgl. Rempel et al. 1985). Positiv hervorzuheben ist weiterhin, dass die kombinierten Konstrukte eine adäquate Multidimensionalität zur Operationalisierung von Vertrauen aufweisen und es in den konkreten Bezug zum Konsumenten und zur Datensammlung stellen.

Mangels einer passenden aktuellen wirtschaftspsychologischen Operationalisierung und aufgrund einer hinreichenden Eignung der dargestellten Konstrukte „kognitives Vertrauen“ und „emotionale Verletzung“ sowie einer direkten Einbettung in den Datenmanagementkontext wird im Rahmen dieser Arbeit trotz der genannten Defiziten die wirtschaftswissenschaftliche Operationalisierung nach Martin et al. und Kollegen (2017) verwendet.

Relevant für die Betrachtung von Konsumentenvertrauen ist zudem, dass sich Vertrauen in höheren Abstraktionsebenen (z.B. Branchenvertrauen, Kanalvertrauen) auf untergeordnete Kontexte auswirkt (Holzmüller et al. 2006). Durch den Abgleich mit kognitiven Skripten werden gewisse Erwartungen auf eine spezifische Geschäftsbeziehung übertragen (Holzmüller et al. 2006; Nooteboom 2002). Dies impliziert kanalspezifische Besonderheiten bei der Betrachtung von Konsumentenvertrauen im E-Commerce (Weiber und Egner-Duppich 2006; Grabner-Kräuter und Fladnitzer 2006), der sich zwar nicht grundlegend, wohl aber teilweise vom klassischen Handel unterscheidet. Auch das Marketingverständnis ist online kein anderes, sondern wird lediglich durch die Möglichkeiten elektronischer Informationstechnologien ergänzt (Kollmann 2013).

Im E-Commerce-Kontext ist Konsumentenvertrauen besonders relevant (Bapna et al. 2017; Clemons et al. 2016; Schubach et al. 2017) und gilt als ein Haupttreiber für Kundenbindung im Internet (Urban et al. 2009). Es unterliegt dabei kanalspezifischen Besonderheiten (Zentes et al. 2006) und ist schwieriger aufzubauen (Bhattacherjee 2002). Dies ist darauf zurückzuführen, dass Onlinetransaktionen durch besonders hohe Unsicherheit (Rice 2012; Hoffman et al. 1999) und Informationsasymmetrie (Clemons et al. 2016) bei gleichzeitigem Information-Overload (Hoffmann et al. 2014) gekennzeichnet sind. Zudem setzen Onlinekäufe oft das Teilen sensibler Daten voraus (Bhattacherjee 2002), was eine vertrauenskritische Situation darstellt (Weiber und Egner-Duppich 2006). Mangelnde Vertrauenswürdigkeit geht mit niedrigerer Zahlungsbereitschaft und Kaufabbrüchen einher (Bapna et al. 2017). Vertrauen kann online durch die Garantie von Privatsphäre und Sicherheit generiert werden (Schubach et al. 2017). Auch das Website-Design (Schlosser et al. 2006) sowie Third-Party-Bewertungen und Gütesiegel (Noll und Winkler 2004; Clemons 2007) können Vertrauen fördern. Mit dem Vertrauen erhöht sich auch die Bereitschaft des Konsumenten, persönliche Informationen preiszugeben (McKnight et al. 2002). Folglich hat es nicht nur direkte Relevanz für die Kundenbindung, sondern unterstützt auch eine datenbasierte CRM-Optimierung.

Bei Onlinekäufen werden – bewusst und unbewusst – besonders viele persönliche Daten offengelegt (Morlok et al. 2018). Auch entstehen gänzlich neue Datenarten wie etwa Verweilzeiten oder Klickverhalten (Mertens et al. 2017). Dies macht eine Betrachtung des Konsumentenvertrauens in diesem Kontext besonders relevant, denn schon „the very act of data collection, whether it is legal or illegal, is the starting point of various information privacy concerns.“ (Malhotra et al. 2004, S. 338).

2.2 Datenwertschöpfung bei Onlinehändlern

Marketing ist zunehmend datenbasiert (Martin et al. 2017) und verwendetet Kundenprofile zur Kommunikations- und Angebotspersonalisierung (Stephan und Werther 2013). Solche Instrumente werden auch speziell für das Kundenbindungsmanagement immer relevanter (Zhang et al. 2011). Daten gelten mitunter sogar als neue Währungsart und moderne Technologien fördern die Effektivität datengetriebener Wissensgenerierung (Morlok et al. 2018).

Die Vorteile von Onlinehändlern bei der Datenwertschöpfung führen zu rasanten Fortschritten im Online-Marketing (Bloching et al. 2012). Big Data im Onlineumfeld bietet sogar das Potenzial, latente Konstrukte wie die Kundenzufriedenheit über neue Messmethoden zu erfassen (Tirunillai und Tellis 2014).

Als ein Vorreiter der Datenwertschöpfung gilt Amazon, der bedeutendste Onlinehändler in Deutschland. Laut einer IFH-Studie von 2019 kaufen über 90% der deutschen Onlinekäufer bei dem Händler (Stüber et al. 2019). Amazon sammelt und verwendet u.a. Informationen zum Kauf- und Interaktionsverhalten sowie Cookies, um maximale Kundenorientierung zu gewährleisten. Diese Informationen beruhen sowohl auf explizit durch den Kunden angegebenen Daten als auch auf automatisch aufgezeichneten Nutzungsdaten und Daten aus externen Quellen (Amazon.de 2018c, 2018a, 2018b).

Die systematische Wissensgenerierung aus den gespeicherten Kundendaten wird in der aktuellen Literatur als Database-Marketing bezeichnet. Hierbei werden vor allem personenbezogene Daten wie Adressdaten, Kaufhistorien und Nutzungsverhalten erhoben und genutzt. Das Database-Marketing dient u.a. der Loyalitäts- und Kundenbindungssteigerung. Hierfür bedienen sich Onlinehändler primär elektronischer Kundenbindungsmaßnahmen, deren technische Implementation über eCRM-Systeme erfolgt. So betreiben Onlinehändler ein sogenanntes One-to-One-Marketing (Kollmann 2013), womit dem Bedürfnis der Konsumenten nach steigender Individualisierung nachgegangen wird (Homburg und Bruhn 2017). Durch das CRM bzw. eCRM lassen sich im Kundenbeziehungsverlauf kontinuierlich weitere Daten sammeln, die eine noch stärkere Individualisierung der Kundenbeziehung ermöglichen (Kollmann 2013).

Der Erfolg des E-Commerce und die Chancen, die sich durch Big Data ergeben, bergen jedoch auch Risiken. Cookies beispielsweise können zur Bedrohung der Privatsphäre werden (Miyazaki 2008). Laut einer Studie von (idealo 2018) ist der E-Commerce seinen Konsumenten voraus. Diese sind durch die Datensammlung verunsichert. Sie haben Angst, zum „gläsernen Kunden“ zu werden (idealo 2018). Auch die regulatorischen Entwicklungen in Gestalt der DSGVO unterstreichen die Wichtigkeit von Datenschutz und beschränken (Online-)Händler in ihrer Datenwertschöpfung (Das Europäische Parlament und Der Rat der Europäischen Union 2018a). Umso wichtiger sind eindeutige Signale des Unternehmens bezüglich adäquater Datenschutzmaßnahmen, da sie das Konsumentenvertrauen erhöhen (Tang et al. 2008).

Solche Signale können beispielsweise über Datenschutzerklärungen vermittelt werden (Tang et al. 2008). Obwohl Datenschutz für Konsumenten ein wichtiges Thema ist (Sidgman und Crompton 2016), werden Datenschutzerklärungen kaum gelesen bzw. nicht verstanden (Martin 2013; McDonald und Cranor 2008; Bakos et al. 2014). Die DSGVO soll diese verständlicher machen, erfordert aber gleichzeitig tendenziell längere Texte (Das Europäische Parlament und Der Rat der Europäischen Union 2018a). Die Konsequenzen auf das Privatsphäreempfinden von Konsumenten sind daher fraglich.

2.3 Privatsphäre und wahrgenommenes Datenschutzrisiko

Personenbezogene Daten sind ein „double-edged sword“ (Malhotra et al. 2004, S. 336). Einerseits bieten sie über Individualisierungsmaßnahmen einen Nutzen für Kunden. Andererseits bedrohen sie dessen Privatsphäre (Malhotra et al. 2004) und erhöhen seine Vulnerabilität (Martin et al. 2017), denn bei der integrierten Datenauswertung kann neben marketingrelevanten Informationen implizit auch hochgradig Privates extrahiert werden (Wedel und Kannan 2016). Besonders kritisch ist auch das Teilen von Kundeninformationen zwischen Geschäftspartnern zur aggregierten Auswertung (Menon und Sarkar 2016). Datenwertschöpfung kann daher negative Auswirkungen auf die Unternehmensperformance haben, wenn sie nicht reflektiert und kundenorientiert durchgeführt wird (Martin et al. 2017). Es gilt, das Verhältnis von nutzenmaximierender Datenwertschöpfung und der Achtung der Privatsphäre über Datenschutz auszubalancieren (Eling 2017; Wedel und Kannan 2016). Die Forschung liegt hierbei hinter der praktisch bereits stattfindenden Datenwertschöpfung zurück (Martin und Murphy 2017).

Durch die datengetriebenen Entwicklungen haben Privatsphäre und Datenschutz im Marketing an Relevanz gewonnen (Martin und Murphy 2017), was durch technologische Neuerungen stetig verstärkt wird (Friedewald 2018). Privatsphäre ist – ähnlich wie Vertrauen – ein breites Konzept, dessen einheitliche Definition schwierig ist (Martin und Murphy 2017; Martin et al. 2017; Bélanger und Crossler 2011; Smith et al. 2011). Für das Marketing ist nach aktueller Literatur insbesondere die informationsbezogene Privatsphäre relevant (Martin und Murphy 2017). Bélanger und Crossler (2011) definieren diese unter Berufung auf Clarke (1999) als „the interest an individual has in controlling, or at least significantly influencing, the handling of data about themselves“ (S. 1018). Im Konsumentenkontext wird sie insbesondere hinsichtlich kundenseitiger Privatsphärebedenken untersucht (Martin et al. 2017; Bélanger und Crossler 2011). Diese beschreiben, wie eine Person die Achtung informationsbezogener Privatsphäre durch ein Unternehmen wahrnimmt (Malhotra et al. 2004).

Martin et al. (2017) bemängeln, dass Privatsphäre ein diffuses Konzept ist, das die psychologische Einstellung gegenüber Datenwertschöpfung von Unternehmen nicht ausreichend erfassen kann. Sie schlagen deshalb vor, die Auswirkungen von unternehmerischer Datenwertschöpfung auf Konsumenten nicht über Privatsphärebedenken, sondern über die empfundene Vulnerabilität, die beim Konsumenten durch Datenwertschöpfung entsteht, zu analysieren.

Konsumenten können bereits gegenüber der reinen Sammlung ihrer Daten Bedenken entwickeln (Malhotra et al. 2004). Negative Effekte durch unternehmerische Datenwertschöpfung beruhen eher auf der Angst des Konsumenten vor potenziellen Schäden als auf tatsächlichen Schäden (Scharf 2007). Martin et al. (2017) sprechen in diesem Zusammen von „data access vulnerability“ [S. 39, dt.: wahrgenommenes Datenzugriffsrisiko]. Das wahrgenommene Datenzugriffsrisiko ist definiert als „customer expectation of susceptibility to the harm that can come from the disclosure of their personal data“ (Martin et al. 2017, S. 42) und kann sowohl negative kognitive als auch emotionale Reaktionen beim Konsumenten hervorrufen (Martin et al. 2017).

Die negativen Auswirkungen des wahrgenommenen Datenzugriffsrisikos lassen sich mit der Gossip-Theorie nach Dunbar (2004) und Foster (2004) erklären. Diese beschreibt, wie Menschen auf die Sammlung und Verwendung ihrer personenbezogenen Informationen durch Dritte reagieren (Martin et al. 2017). Gossip (dt. Tratsch) meint jegliche wertende Kommunikation über einen nicht anwesenden Dritten (Foster 2004; Feinberg et al. 2012). Die negativen Effekte des wahrgenommenen Datenzugriffsrisikos entstehen dadurch, dass das Unternehmen Informationen über den Konsumenten besitzt, die es gegen ihn einsetzen und ihn damit abwerten könnte. Hierdurch fühlt der Konsument sich verletzbar (Martin et al. 2017), was wiederum eine Vertrauenserosion hervorrufen kann (Turner et al. 2003). Das wahrgenommene Datenzugriffsrisiko wirkt sich zum einen auf das Konsumentenvertrauen aus. Zum anderen bewirkt es final u.a. erhöhte Wechselbereitschaft und negatives Weiterempfehlungsverhalten (Martin et al. 2017). Diese Dimensionen finden sich sinngemäß auch im Konstrukt der Kundenbindung in der aktuellen Literatur nach Homburg und Bruhn (2017) wieder. Folglich kann von einem Zusammenhang zwischen wahrgenommenen Datenzugriffsrisiko und Kundenbindung ausgegangen werden. Martin et al. (2017) zeigen, dass Vertrauen hier zudem eine Mediatorrolle einnimmt. Auch andere Autoren beschreiben Vertrauen als mediierend für Verhalten im E-Commerce-Kontext (z.B. Clemons et al. 2016).

Weiterhin identifizieren Martin et al. (2017) die Transparenz eines Unternehmens im Umgang mit Kundendaten als relevanten Faktor im Zusammenhang mit wahrgenommenem Datenzugriffsrisiko und Konsumentenvertrauen. Insbesondere negative emotionale Auswirkungen beim Konsumenten können durch Transparenz ausgebremst werden (Martin et al. 2017). Wie bereits erwähnt, beschreibt auch Neumann (2007) die Ehrlichkeit eines Unternehmens als wichtige Dimension des Konsumentenvertrauens. Weiterhin sind Unternehmen durch die DSGVO zu mehr Transparenz und somit ehrlichem Verhalten angehalten (Das Europäische Parlament und Der Rat der Europäischen Union 2018b). Insbesondere Datenschutzerklärungen können Vertrauen schaffen wenn sie die konsumentenseitigen Datenschutzerwartungen erfüllen (Milne und Bahl 2010). Der Ehrlichkeit eines Unternehmens fällt also eine besondere Bedeutung zu. Daher soll der Faktor in dieser Studie zusätzlich gesondert betrachtet werden.

2.4 Moderatoren im Kontext von Big Data und Konsumentenvertrauen

Im technologischen Forschungsumfeld spielen demographische Merkmale bei diversen Fragestellungen eine Rolle. In diesem Kontext ist oft von *Digital Natives* die Rede (z.B. Hoffmann et al. 2014; Joiner et al. 2013).

Die Generation der Digital Natives, die mit modernen Technologien aufgewachsen ist, unterscheidet sich maßgeblich von den *Digital Immigrants*, die nicht mit der heutigen Technologie aufgewachsen sind (Prensky 2001b, 2001a). Für Handelsunternehmen – insbesondere im E-Commerce – ist es essentiell, beide Gruppen anzusprechen (Vodanovich et al. 2010).

Jüngere Personen sind Technologie gegenüber positiver eingestellt als Ältere (Joiner et al. 2013) und ältere Personen analysieren potenzielle Risiken einer Onlinetransaktionen besonders kritisch (Hoffmann et al. 2014). Aber auch innerhalb der Digital Natives gibt es Unterschiede. So teilen Joiner et al.

(2013) Digital Natives in zwei Subgenerationen auf: die erste Generation mit Geburtsdatum nach 1980 in Anlehnung an Prensky (2001a) und die zweite Generation mit Geburtsdatum nach 1993. Die Autoren stellen fest, dass die zweite Generation das Internet sowohl häufiger nutzt als diesem gegenüber auch positiver eingestellt ist (Joiner et al. 2013). Auch haben Digital Natives eine andere Wahrnehmung von Privatsphäre, geben Daten eher preis (Palfrey und Gasser 2008) und bauen Vertrauen online anders auf (Hoffmann et al. 2014).

Die oben genannten Generationsdifferenzen sowie länderspezifisch-kulturelle Unterschiede vertrauensbegründender Faktoren (vgl. Clemons et al. 2016) und die besonders kritische Haltung der Deutschen zum Datenschutz (vgl. Morey et al. 2015) implizieren, dass auch die empfundene Wichtigkeit des Themas eine Rolle im Wirkkomplex dieser Studie einnimmt. Altersunterschiede und die subjektive Wichtigkeit von Datenschutz sind im digitalen Umfeld also aktueller Literatur nach von hoher Relevanz und lassen einen moderierenden Einfluss auf die Wirkung des wahrgenommenen Datenzugriffsrisikos vermuten.

2.5 Hypothesen

Wie im Theorieteil herausgearbeitet wurde, ist Big Data grundsätzlich nützlich für das CRM. Es kann jedoch auch negative Folgen für Konsumentenvertrauen und Kundenbindung haben (Martin et al. 2017; Zhang et al. 2011). Insbesondere die Arbeiten von Neumann (2007) sowie Martin et al. (2017) haben gezeigt, dass für die Kundenbindung insbesondere das Konsumentenvertrauen entscheidend ist, ergänzt durch die Ehrlichkeit des Unternehmens sowie das wahrgenommene Datenzugriffsrisiko.

In der vorliegenden Studie wurde untersucht, in welchem Zusammenhang diese vier Konstrukte zueinanderstehen. Zunächst wurde geprüft, ob das wahrgenommene Datenzugriffsrisiko sowie die Ehrlichkeit einen direkten Einfluss auf die Kundenbindung haben, oder ob dieser Zusammenhang durch das Konsumentenvertrauen vermittelt wird.

Hypothese 1a:	*Der Zusammenhang zwischen wahrgenommenem Datenzugriffsrisiko und Kundenbindung wird durch das Konsumentenvertrauen mediiert.*

Hypothese 1b:	*Der Zusammenhang zwischen Ehrlichkeit und Kundenbindung wird durch das Konsumentenvertrauen mediiert.*

Anschließend wurden die vier Konstrukte in ein gemeinsames Pfadmodell integriert und dessen Gültigkeit geprüft.

Hypothese 2:	*Das wahrgenommene Datenzugriffsrisiko und die Ehrlichkeit erklären gemeinsam das Konsumentenvertrauen, welches wiederum die Kundenbindung erklärt. Nur die Ehrlichkeit, aber nicht das Datenzugriffsrisiko, hat neben dem indirekten auch einen direkten Einfluss auf die Kundenbindung.*

In der Literatur haben sich vor allem das Alter und die Datenschutzwichtigkeit als wesentliche Moderatoren für die hier untersuchten Zusammenhänge herausgestellt

Hypothese 3a:	*Die Zusammenhänge zwischen den zentralen Konstrukten werden durch das Alter moderiert.*

Hypothese 3b:	*Die Zusammenhänge zwischen den zentralen Konstrukten werden durch die Datenschutzwichtigkeit moderiert.*

Schließlich wurde geprüft, inwieweit sich die beiden potenziellen Moderatoren Alter und Datenschutzwichtigkeit gegenseitig beeinflussen.

Hypothese 4:	*Die Interaktion zwischen dem Alter und der Datenschutzwichtigkeit hat einen Einfluss auf die Ausprägung der vier untersuchten Konstrukte.*

3 Methodik

3.1 Durchführung der Untersuchung

Die Datenerhebung erfolgte als standardisierte Online-Umfrage[1]. Diese wurde über das Portal www.soscisurvey.de durchgeführt. Die Befragung dauerte im Durchschnitt 6.2 Minuten. Die Teilnehmer wurden über persönliche Kontakte sowie Postings in sozialen Netzwerken rekrutiert.

Nach Begrüßung und Initialinstruktion waren zwei Fragen zur Kaufhäufigkeit bei Amazon und den Gründen hierfür zu beantworten. Anschließend sollten Teilnehmer eine allgemeine Aussage zur Wichtigkeit von Datenschutz bewerten.

Nach der Aussage zum Datenschutz folgte eine Seite mit dem Stimulusmaterial zum wahrgenommenen Datenzugriffsrisiko. Die Teilnehmer wurden gebeten, sich dieses aufmerksam durchzulesen, bevor sie mit der Befragung fortfahren. Anschließend war die Skala zum wahrgenommenen Datenzugriffsrisiko zu beantworten. Nach einer weiteren kurzen Instruktion wurden die übrigen Konstrukte abgefragt (wahrgenommene Ehrlichkeit des Unternehmens, Konsumentenvertrauen, Kundenbindung). Abschließend waren Angaben zur Person und Amazon Prime-Mitgliedschaft zu machen.

3.2 Operationalisierung der relevanten Konstrukte

Die *Datenschutzwichtigkeit* wurde mit einem Item („Datenschutz ist mir wichtig.“) operationalisiert. Das *wahrgenommene Datenzugriffsrisiko* wurde anhand der ins Deutsche übersetzten Skala *Vulnerability* nach Martin et al. (2017) erhoben. Die Skala enthält fünf Adjektive (unsicher, entblößt, bedroht, verletzbar, anfällig), für die der Grad der Zustimmung in Bezug auf die Aussage „Durch die persönlichen

[1] Für die Unterstützung bei der Datenerhebung danken wir Jan Boddenberg, Hannah Erlebach, Caroline Kling und Ricardo Rodriguez.

Informationen, die Amazon über mich hat, fühle ich mich: …“ angeben wurde. Für die Dimension *Ehrlichkeit* wurde die Operationalisierung nach Neumann (2007) übernommen. Hier wurden vier Adjektive (rechtschaffend, ehrhaft, aufrichtig, ehrlich), bezogen auf die Aussage „Das Unternehmen Amazon ist …“, bewertet. Das *Konsumentenvertrauen* wurde anhand der beiden von Martin et al. (2017) verwendeten, jeweils vier Items umfassenden, Dimensionen *Cognitive Trust* (z.B. „Ich vertraue der Firma.“) und *Emotional Violation* (z.B. „Ich fühle mich ausgenutzt.“) erhoben. Für die Berechnung des Gesamtwertes von Konsumentenvertrauen wurden die negativ formulierten Items der Dimension Emotional Violation invertiert. Die Messung der *Kundenbindung* erfolgt über Subskalen zu Wiederkaufabsicht, Zusatzkaufabsicht und Weiterempfehlungsabsicht, analog zu Neumann (2007), mit je drei Items pro Subskala. Die Items sind angelehnt an die Inventare für Kaufabsichten von Giering (2000) sowie Sirohi et al. (1998) und die Inventare für Weiterempfehlungsabsichten von Giering (2000) sowie Zeithaml et al. (1996). Alle Items der hier aufgeführten Konstrukte wurden auf einer 7-stufigen Antwortskala (1 = „trifft überhaupt nicht zu“ bis 7 = „trifft vollkommen zu“) bewertet.

3.3 Stichprobe

Die Auswertungsstichprobe bestand aus N = 128 Teilnehmern. Das Durchschnittsalter betrug 28.25 Jahre (SD = 10.6). 61.7% der Teilnehmer waren weiblich, 35.9% männlich und 3 (2.3%) haben ihr Geschlecht nicht angeben. Als höchsten Bildungsabschluss haben 88.5% das Abitur oder ein abgeschlossenes Studium genannt.

52.3% der Teilnehmer nutzen Amazon Prime, 42.2% nutzen dies nicht und 7 (5.5%) haben hierzu keine Angabe gemacht. Die Kaufhäufigkeit bei Amazon haben 12.0% mit nie oder sehr selten angegeben, 40.8% mit selten oder gelegentlich und 47.2% der Teilnehmer kaufen oft, sehr oft oder regelmäßig bei Amazon.

4 Ergebnisse

4.1 Deskriptive Befunde

Tabelle 1 zeigt die deskriptiven Ergebnisse für die untersuchten Konstrukte, sowie für die Kontrollvariablen Geschlecht, Alter und Datenschutzwichtigkeit.

Tabelle 1: Mittelwert und Standardabweichung, Interkorrelationen und Reliabilität

		M	SD	1	2	3	4	5	6	7
1	Geschlecht	.63	.48							
2	Alter	28.25	10.63	-.01						
3	Datenschutzwichtigkeit	5.35	1.46	.15	.16					
4	Ehrlichkeit	3.46	1.35	.09	-.10	-.06	*(.90)*			
5	wahrg. Datenzugriffsrisiko	3.26	1.46	.08	.15	.31**	.04	*(.93)*		
6	Konsumentenvertrauen	4.42	1.19	.10	-.21*	-.19*	.43**	-.63**	*(.88)*	
7	Kundenbindung	4.53	1.49	.20*	-.18*	-.18*	.55**	-.23*	.55**	*(.95)*

Anmerkung: N=128; Reliabilität (Cronbachs Alpha) ist in Klammern dargestellt;
* p ≤ .05 (2-seitig); ** p ≤ .01 (2-seitig)

Quelle: Eigene Darstellung

Die Reliabilitäten der vier mit Hilfe psychometrischer Fragebogen erfassten Konstrukte sind mit Cronbachs Alpha zwischen .88 und .95 sehr gut. Die Interkorrelationen zeigen, dass vor allem zwischen dem Konsumentenvertrauen und der Kundenbindung ein hoher Zusammenhang besteht ($r = .55$, $p < .001$). Auch die Ehrlichkeit weist hohe Zusammenhänge mit dem Konsumentenvertrauen ($r = .43$, $p < .001$) und der Kundenbindung ($r = .55$, $p < .001$) auf. Der höchste Zusammenhang besteht zwischen dem wahrgenommenen Datenzugriffsrisiko und dem Konsumentenvertrauen ($r = -.63$, $p < .001$).

4.2 Konsumentenvertrauen als Mediator

Der standardisierte Gesamteffekt vom Datenzugriffsrisiko auf die Kundenbindung liegt bei $\beta = -.231$ (CI95% -.408 – -.042, p2-seitig = .011), wobei der direkte Zusammenhang $\beta = .196$ (CI95% -.014 – .410, p2-seitig = .070) und der indirekte Zusammenhang $\beta = -.427$ (CI95% -.601 – -.289, p2-seitig = .001) beträgt. Da hier der Gesamtzusammenhang und der direkte Zusammenhang unterschiedliche Vorzeichen haben ist anzunehmen, dass ein Suppressoreffekt vorliegt und der Gesamtzusammenhang neben dem Mediator Konsumentenvertrauen auch noch durch mindestens einen weiteren Einflussfaktor (z.B. Ehrlichkeit) zustande kommt.

Hypothese 1a kann somit bestätigt werden, da kein direkter Zusammenhang zwischen dem wahrgenommenen Datenzugriffsrisiko und der Kundenbindung besteht bzw. der Gesamtzusammenhang nur durch andere Variablen zu erklären ist, wie der Suppressoreffekt zeigt.

Der standardisierte Gesamteffekt der Ehrlichkeit auf die Kundenbindung liegt bei $\beta = .545$ (CI95% .421 – .651, p2-seitig = .001), der direkte Zusammenhang beträgt $\beta = .378$ (CI95% .242 – .509, p2-seitig = .001) und der indirekte Zusammenhang $\beta = .167$ (CI95% .091 – .255, p2-seitig = .001).

Hypothese 1b kann ebenfalls bestätigt werden, da ein signifikanter indirekter Effekt vorliegt. Es handelt sich hier jedoch um eine partielle Mediation, da auch der direkte Effekt signifikant ist.

4.3 Pfadmodell

Das in Abbildung 1 dargestellte Pfaddiagramm zeigt die Ergebnisse der Pfadanalyse.

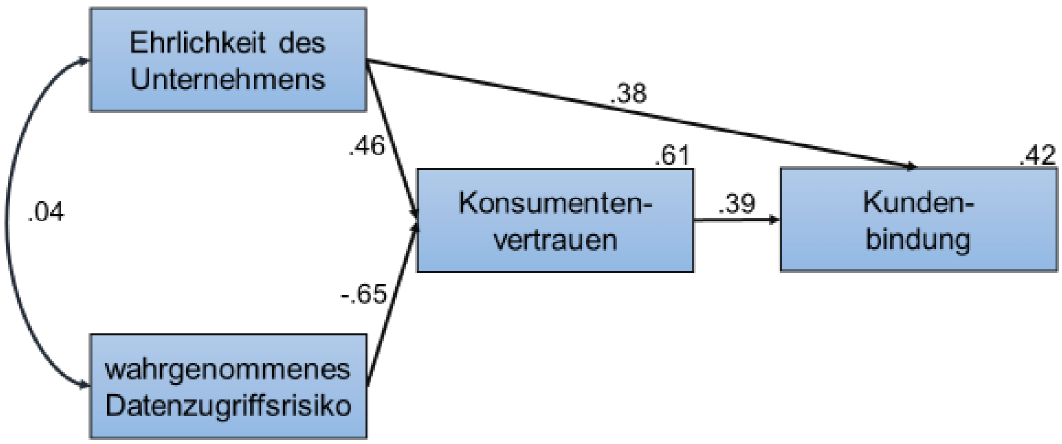


Abbildung 1: Pfadmodell mit standardisierten Koeffizienten
Quelle: Eigene Darstellung

Die Prüfung des Pfadmodells hat mit den Fit-Indikatoren X^2 = .001 (df = 1, p = .973), CFI = 1.00 und NFI = 1.00 sowie RMSEA = .000 und SRMR = .038 eine fast perfekte Modellgüte ergeben. *Hypothese 2* kann somit bestätigt werden.

4.4 Alter und Datenschutzwichtigkeit als Moderatoren

Als Moderatorvariablen wurden das Alter sowie die subjektive Datenschutzwichtigkeit verwendet, um zu untersuchen, ob diese die im Pfadmodell (Abbildung 1) angenommenen Zusammenhänge zwischen den Konstrukten beeinflussen.

Beim Alter konnte für keinen der vier untersuchten Zusammenhänge ein Moderator-Effekt gefunden werden. Für den Zusammenhang zwischen wahrgenommenem Datenzugriffsrisiko und Konsumentenvertrauen weist der Interaktionsterm mit dem Alter ein β = .010 (p = .893) auf. Beim Zusammenhang zwischen Ehrlichkeit des Unternehmens und dem Konsumentenvertrauen beträgt das β = .103 (p = .218) sowie bei der Ehrlichkeit und der Kundenbindung β = .018 (p = .820). Auch der Zusammenhang zwischen dem Konsumentenvertrauen und der Kundenbindung wird nicht durch das Alter moderiert, hier weist der Interaktionsterm β = .130 (p = .104) auf. *Hypothese 3a* ist somit abzulehnen, da das Alter keinen moderierenden Einfluss auf die relevanten Zusammenhänge zwischen den vier untersuchten Konstrukten ausübt.

Bei der Betrachtung der subjektiven Datenschutzwichtigkeit als Moderator auf die relevanten Zusammenhänge im Modell zeigt sich ein gemischtes Ergebnis. Bei zwei der untersuchten Zusammenhänge zeigte sich kein Moderator-Effekt der Datenschutzwichtigkeit (Datenzugriffsrisiko und Konsumentenvertrauen: β = .059, p = .411; Konsumentenvertrauen und Kundenbindung: β = .044, p = .565). Bei den beiden Zusammenhängen der Ehrlichkeit mit dem Konsumentenvertrauen und der Kundenbindung konnte hingegen eine signifikante Moderation durch die Datenschutzwichtigkeit gefunden werden, wie in Tabelle 2 zu sehen ist.

Tabelle 2: Ergebnisse der hierarchischen Regression zur Prüfung der Moderation

Schritt	Prädiktoren	Konsumentenvertrauen BETA	Konsumentenvertrauen ΔR^2	Kundenbindung BETA	Kundenbindung ΔR^2
1	Ehrlichkeit (UV)	.422**		.535**	
	Datenschutzwichtigkeit (M)	-.163*		-.148*	
			.214**		.319**
2	Ehrlichkeit (UV)	.396**		.515**	
	Datenschutzwichtigkeit (M)	-.156*		-.143*	
	Interaktion	.297**		.231**	
			.088**		.053**

Anmerkung: N=128; * p ≤ .05 (2-seitig); ** p ≤ .01 (2-seitig)

Quelle: Eigene Darstellung

Abbildung 2 zeigt das Interaktionsdiagramm für die Moderation des Zusammenhangs zwischen Ehrlichkeit und Konsumentenvertrauen durch die subjektive Datenschutzwichtigkeit. Bei Teilnehmern mit einer niedrig eingeschätzten subjektiven Datenschutzwichtigkeit zeigt sich kein Unterschied in der Höhe des Konsumentenvertrauens im Vergleich von niedriger und hoher Ehrlichkeit. Bei Teilnehmern mit einer hohen Datenschutzwichtigkeit gibt es einen deutlichen Unterschied. Diejenigen, die in dieser Gruppe eine niedrige Ehrlichkeit wahrnehmen, zeigen ein deutlich reduziertes Konsumentenvertrauen. Wenn hingegen die Ehrlichkeit als hoch wahrgenommen wird, resultiert das insgesamt höchste Konsumentenvertrauen.

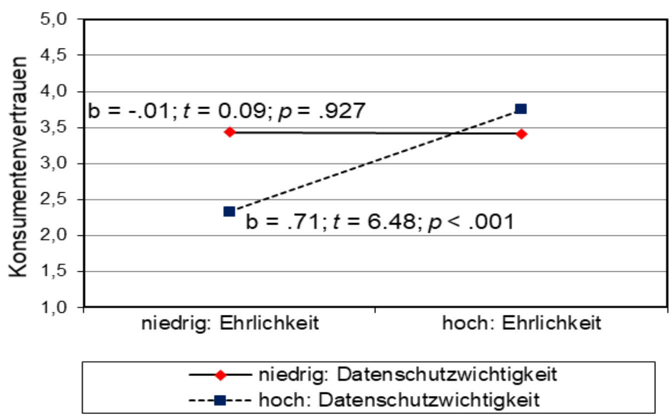


Abbildung 2: Moderationseffekt der Datenschutzwichtigkeit auf den Zusammenhang zwischen Ehrlichkeit und Konsumentenvertrauen

Quelle: Eigene Darstellung

Bei der Darstellung der Ergebnisse des Moderationseffekts der Datenschutzwichtigkeit auf den Zusammenhang zwischen Ehrlichkeit und Kundenbindung ergibt sich ein ähnliches Bild (s. Abbildung 3). Hier zeigt sich ebenfalls ein deutlicher Unterschied zwischen niedriger und hoher Ehrlichkeit in der Gruppe der Teilnehmer mit hoher Datenschutzwichtigkeit. Allerdings ist hier auch ein geringfügiger Unterschied zwischen hoher und niedriger Ehrlichkeit in der Gruppe der Teilnehmer mit niedriger Datenschutzwichtigkeit zu erkennen, wobei dieser Unterschied nicht signifikant ist (b = .22, p = .075).

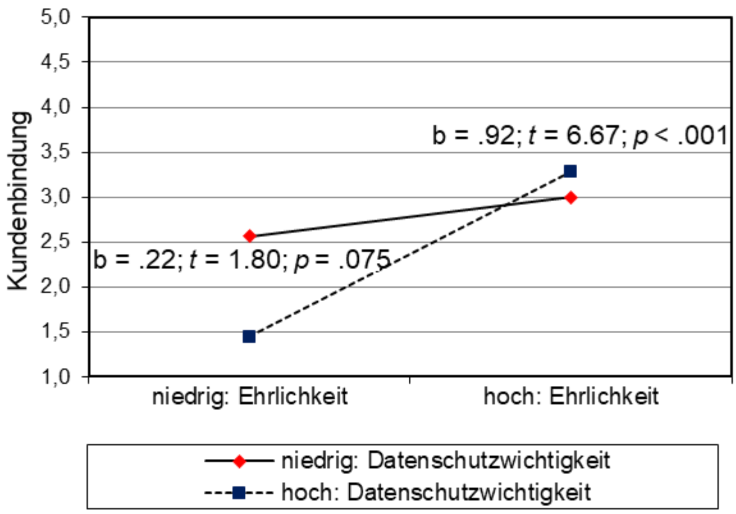


Abbildung 3: Moderationseffekt der Datenschutzwichtigkeit auf den Zusammenhang zwischen Ehrlichkeit und Kundenbindung
Quelle: Eigene Darstellung

Hypothese 3b kann teilweise bestätigt werden, da die Datenschutzwichtigkeit zumindest die beiden Zusammenhänge zwischen der Ehrlichkeit und dem Konsumentenvertrauen sowie der Kundenbindung moderiert.

Abschließend wurde überprüft, inwieweit das Alter und die Datenschutzwichtigkeit gemeinsam die Ausprägung der vier untersuchten Konstrukte beeinflussen. Bei drei Konstrukten konnte keine Interaktion der Datenschutzwichtigkeit und des Alters gefunden werden (Ehrlichkeit: β = -.055, p = .572; Konsumentenvertrauen: β = -.101, p = .281; Kundenbindung: β = -.107, p = .258). Nur die Ausprägung des wahrgenommenen Datenzugriffsrisikos weist eine signifikante Wechselwirkung auf (s. Tabelle 3).

Tabelle 3: Ergebnisse der hierarchischen Regression zur Prüfung der Moderation durch das Alter

Schritt	Prädiktoren	w. Datenzugriffsr. BETA	ΔR^2
1	Datenschutzwichtigkeit (UV)	,284**	
	Alter (M)	,109	
			,103**
2	Datenschutzwichtigkeit (UV)	,288**	
	Alter (M)	,041	
	Interaktion	,201*	
			.036*

Anmerkung: N=128;
* p ≤ .05 (2-seitig); ** p ≤ .01 (2-seitig)

Quelle: Eigene Darstellung

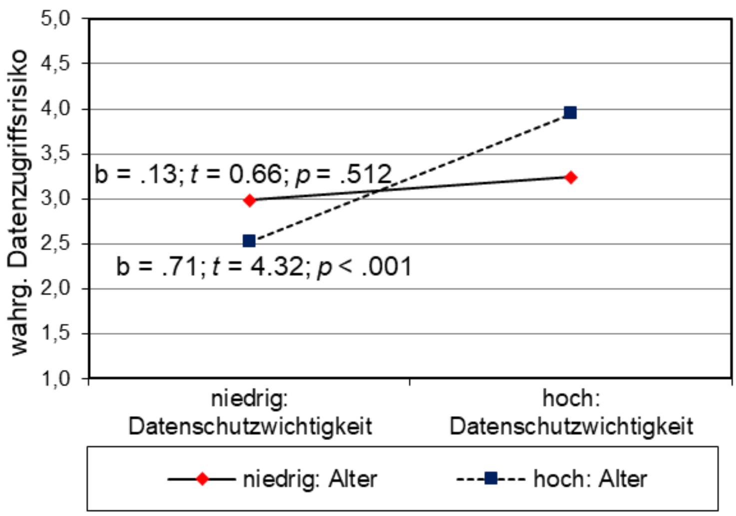


Abbildung 4: Moderationseffekt des Alters auf den Zusammenhang zwischen Datenschutzwichtigkeit und wahrg. Datenzugriffsrisiko
Quelle: Eigene Darstellung

Während in der Gruppe der jungen Teilnehmer kein Unterschied des wahrgenommenen Datenzugriffsrisikos in Abhängigkeit von der Datenschutzwichtigkeit feststellbar ist, weisen ältere Teilnehmer mit hoher Datenschutzwichtigkeit deutlich höhere Werte im wahrgenommenen Datenzugriffsrisiko auf als ältere Teilnehmer mit einer geringen Datenschutzwichtigkeit.

Hypothese 4 kann somit nur teilweise bestätigt werden, da lediglich bei der Ausprägung des wahrgenommenen Datenzugriffsrisikos eine Wechselwirkung zwischen Datenschutzwichtigkeit und Alter vorliegt, jedoch nicht bei den anderen drei Konstrukten.

5 Diskussion

Das Pfadmodell, das eine sehr gute Modellanpassung aufweist, bestätigt die Ergebnisse der Mediationsanalysen, wonach der Einfluss des wahrgenommenen Datenzugriffsrisikos auf die Kundenbindung vollständig über das Konsumentenvertrauen vermittelt wird und beim Einfluss der Ehrlichkeit des Unternehmens auf die Kundenbindung eine partielle Mediation durch das Konsumentenvertrauen vorliegt.

Die Moderationsanalysen für die Zusammenhänge zwischen den Konstrukten haben nur für die subjektive Datenschutzwichtigkeit signifikante Ergebnisse ergeben, wohingegen das Alter keinen der vier untersuchten Zusammenhänge moderiert.

Das formulierte Pfadmodell konnte empirisch bestätigt werden. Es konnte also nachgewiesen werden, dass das Konsumentenvertrauen umso geringer ausfällt je höher das wahrgenommene Datenzugriffsrisiko ist. Dies belegt im Einklang mit Martin et al. (2017), dass die Kundendatensammlung zu einer Vertrauenserosion beim Konsumenten führen kann. Dieser Effekt wirkt sich über die Kundenbindung auch auf den ökonomischen Unternehmenserfolg aus.

Problematisch könnte allerdings sein, dass das Konsumentenvertrauen auch bei starkem wahrgenommenen Datenzugriffsrisiko systematisch zu hoch eingeschätzt wurde, da kognitives Vertrauen sinngemäß auch auf der Unternehmenskompetenz beruht (Martin et al. 2017). So wird Amazon als Marktführer sicherlich hohe Kompetenz in seiner Leistungserbringung zugeschrieben. Die Kompetenzeinschätzung ist jedoch vermutlich losgelöst von dem Vertrauen in den Datenumgang des Unternehmens. Diese Vermutung stimmt mit den Überlegungen von McKnight et al. (2002) überein, wonach das Vertrauen in den Datenumgang eines Onlinehändlers nicht dasselbe ist wie das Vertrauen in die Lieferpflichteinhaltung (McKnight et al. 2002). Auch ist zu bemerken, dass Fragebögen zwar eine valide Erfassungsmethode für spezifisches Vertrauen darstellen, die soziale Erwünschtheit von Vertrauen allerdings zu Antworttendenzen führen kann (Petermann und Winkel 2006). Es sollte jedoch das holistische Konsumentenvertrauen, nicht das spezielle Vertrauen in den Datenumgang, untersucht werden. Weiterhin war das wahrgenommene Datenzugriffsrisiko in der Stichprobe ohnehin nicht sehr hoch. Dies könnte daran liegen, dass Onlinekäufer generell freizügiger im Umgang mit Daten sind. Nach Palfrey und Gasser (2008) ist dies zumindest bei der jungen Generation der Digital Natives der Fall, die einen Großteil der Stichprobe ausmachen.

Besonders überraschend ist in diesem Zusammenhang, dass das Alter in der Stichprobe keinen moderierenden Einfluss auf die Beziehungen der relevanten Konstrukte hatte. Dies steht im Widerspruch zu früherer Forschung, die Generationsunterschiede als bedeutsame Variable bei digitalen Vertrauensverhältnissen auffasst (z.B. Hoffmann et al. 2014). Eine Erklärung könnte sein, dass insbesondere ältere Menschen sich dem Datenzugriffsrisiko gar nicht wirklich bewusst sind und es folglich kaum wahrnehmen, wodurch es keinen Einfluss auf das Konsumentenvertrauen nimmt. Privatsphärebedrohungen durch Datensammlung können schließlich nur empfunden werden, wenn ein Bewusstsein über die Datensammlung herrscht (Foxman und Kilcoyne 1993). Diese Vermutung wird dadurch unterstützt, dass das Bewusstsein der Deutschen über die eigene Datenfreizügigkeit generell lückenhaft ist (Morey et al. 2015). Vermutlich wären ältere Menschen kritischer bezüglich der Datensammlung, wenn sie mehr über die dahinterliegenden Prozesse wüssten. Schließlich geht höheres Alter in der Stichprobe tendenziell auch mit niedrigerem Konsumentenvertrauen einher. Höchstwahrscheinlich sind die vorliegenden Ergebnisse jedoch auf die Tatsache zurückzuführen, dass in der Stichprobe eine linkssteile Altersverteilung herrscht. Eine rein altersorientierte Betrachtung im Digitalkontext ist aber ohnehin problematisch, da sie individuelle Verhaltenskomponenten ausblendet (Palfrey und Gasser 2008; Palfrey 2007).

Abschließend bestätigte sich, dass das Konsumentenvertrauen eine wichtige Einflussgröße der Kundenbindung ist. Dies steht im Einklang zur etablierten Theorie von Homburg und Bruhn (2017), die Vertrauen als Teil der Kundenloyalität in die Wirkungskette der Kundenbindung integriert. Auch die Befunde von Neumann (2007) bezüglich der Auswirkungen von Konsumentenvertrauen werden damit unterstützt. Es könnte jedoch grundsätzlich auch sein, dass Kundenbindung und Konsumentenvertrauen aufgrund der Marktführerstellung von Amazon hoch sind und der Zusammenhang bei kleineren Onlineshops anders aussähe. Da es sich bei der Wirkungskette der Kundenbindung jedoch um fundierte Zusammenhänge handelt, ist diese Vermutung zu vernachlässigen.

6 Implikationen

6.1 Implikationen für die Managementpraxis

Sowohl vor dem Hintergrund der Ergebnisse dieser Arbeit als auch der DSGVO ist es für Onlinehändler, aber auch klassische Handelsunternehmen, von höchster Relevanz, sich genauer mit dem eigenen Datenumgang aus Konsumentensicht zu befassen. Mangelnde Beschäftigung mit diesem Thema führt nicht nur unmittelbar über rechtliche Sanktionen, sondern auch über die Schädigung existierender Kundenbeziehungen zu monetären Verlusten. Mit der steigenden gesellschaftlichen Wichtigkeit des Datenschutzes werden diese Effekte potenziell noch stärker.

Das wahrgenommene Datenzugriffsrisiko ist wirtschaftlich relevant und sollte aktiv gemanagt werden. Es hat über die Wirkungskette von Konsumentenvertrauen und Kundenbindung negative Auswirkungen. Da Kundenbindung über den CLV letztlich den ökonomischen Unternehmenserfolg beeinflusst (Homburg und Bruhn 2017; Bruhn 2016), ist das wahrgenommene Datenzugriffsrisiko somit ein Treiber von Kunden- und Unternehmenswert.

Dabei ist die für den Kunden *ersichtliche* Datensammlung und -nutzung entscheidend. Das durch den Kunden *wahrgenommene* Datenzugriffsrisiko muss aktiv verringert werden. Kontaktpunkte, an denen der Kunde mit unternehmerischen Datenwertschöpfungsprozessen in Berührung kommt, müssen so gestaltet sein, dass sie dem Kunden Transparenz und Kontrollmöglichkeiten bieten. Der Kunde muss das Gefühl entwickeln, dass er durch die Preisgabe seiner Daten nicht verwundbar ist, da er sich der konkreten Datensammlung und -nutzung bewusst ist. Dies bestätigen auch die Untersuchungen von Martin et al. (2017).

Hierfür kommen diverse Maßnahmen in Frage: Beispielsweise sollten Kunden darauf aufmerksam gemacht werden, sobald ihre Daten verwendet werden. Außerdem sollte datenschutzbezogene Informationskommunikation kompakt sein, da lange Texte, wie etwa Datenschutzerklärungen, kaum gelesen werden. Gegenüber dem Kunden sollte also eine zusammenfassende Informationsaufbereitung erfolgen. Die offizielle Datenschutzerklärung dient damit primär juristischer Absicherung.

Die differenzierte Wirkung der Ehrlichkeit in Abhängigkeit von der Datenschutzwichtigkeit kann implizieren, dass Onlinehändler sich Klarheit verschaffen müssen, wie wichtig ihren Kunden der Datenschutz ist. Für Plattformen deren Nutzer potenziell keinen nennenswerten Wert auf ihre Privatsphäre legen, werden sich Anstrengung hinsichtlich des Datenschutzes nur wenig bis gar nicht auf das Konsumentenvertrauen und die Kundenbindung auswirken. Dies wird indirekt durch die – wenn überhaupt – nur sehr kurzfristigen Auswirkungen von Datenschutzskandalen auf die Nutzung betroffener Plattformen deutlich. Im Kontrast dazu sollten Onlineunternehmen, die auch Nutzer mit einem hohen Datenschutzbewusstsein haben (z.B. Onlinehändler), in einen von Ehrlichkeit geprägten Umgang bezüglich den erhobenen Kundendaten investieren, da eine von den Nutzern wahrgenommene Ehrlichkeit auch zu gesteigertem Konsumentenvertrauen sowie Kundenbindung führt.

Wie die vorangegangenen Ausführungen zeigen, sollte das wahrgenommene Datenzugriffsrisiko als relevante Einflussgröße auf den unternehmerischen Erfolg ernst genommen und entsprechend gemanagt werden. Es ist naheliegend anzunehmen, dass das Commitment des Top-Managements zu Themen des Datenschutzes hierbei eine wesentliche Rolle einnimmt.

6.2 Limitationen und Ausblick auf zukünftige Forschung

Die im Rahmen der vorgelegten Studie gezogene Stichprobe fällt mit N = 128 verhältnismäßig klein aus, was die Repräsentativität einschränkt. Andererseits legen die deutlichen Signifikanzen nicht nahe, dass eine Verzerrung der Ergebnisse aufgrund zu kleiner Stichprobe vorliegt. Weiterhin wurden die Befragten teilweise über soziale Medien angeworben, was in diesem Teil der Stichprobe eine tendenziöse Einstellung zum Thema Datenschutz bewirken könnte. Allerdings wurden Befragte auch über andere Kanäle akquiriert, wodurch keine generelle Tendenz innerhalb der Stichprobe zu erwarten ist.

Die größte Einschränkung ist in der Operationalisierung zu sehen. Es wurden weitestgehend die Skalen einschlägiger Studien zu dem Thema verwendet (Neumann 2007; Martin et al. 2017). Jedoch bestanden diese für die Konstrukte Ehrlichkeit und wahrgenommenes Datenzugriffsrisiko ausschließlich aus Adjektivlisten. Die Weiterentwicklung der Konstrukte und die Etablierung detaillierterer Skalen in Folgestudien ist wünschenswert. Insbesondere die Entwicklung einer psychologischen Operationalisierung ist ein wichtiges Anliegen zukünftiger Forschung. Zudem ist der Themenkomplex von Onlinekäufen, Privatsphäre, Datenschutz und Konsumentenvertrauen speziell in der Wirtschaftspsychologie kaum untersucht und benötigt mehr Forschung.

Ein wichtiger Forschungsgegenstand hierbei ist die Untersuchung des Bewusstseins von Konsumenten über unternehmerische Datenwertschöpfungspraktiken. Es ist ein eingehendes Verständnis darüber nötig, inwiefern das Datenzugriffsrisiko – abhängig von dem Wissen über Datenwertschöpfungspraktiken – überhaupt wahrgenommen wird. Dieser Zusammenhang ist insbesondere, wenn auch nicht ausschließlich, bei älteren Konsumenten fraglich.

Weiterhin ist darauf hinzuweisen, dass ausschließlich das Internetunternehmen Amazon bzw. dessen Onlineplattform amazon.de betrachtet wurde. Für nachfolgende Studien wäre sicher interessant zu untersuchen, ob es deutliche Unterschiede in den Ergebnissen bei anderen Onlinehändlern gibt. Auch wäre eine Untersuchung von Social-Media-Plattformen wie beispielsweise Facebook, die von vielen Nutzer (und v.a. Nicht-Nutzern) sehr kritisch hinsichtlich ihres Umgangs mit dem Datenschutz gesehen werden, in diesem Themenfeld spannend. Da es hier aber nicht um das Niveau bzw. die Ausprägung der untersuchten Konstrukte, sondern um den Zusammenhang zwischen diesen ging, sollte bereits die Untersuchung von Amazon als eines der aktuell wichtigsten Onlineunternehmen wichtige Erkenntnisse liefern.

Schließlich ist anzumerken, dass die Betrachtung preisbezogener Dimensionen nicht Teil des vorliegenden Beitrags war, da diesem die klassische Definition der Kundenbindung zugrunde liegt. Zudem ging es nicht um eine Untersuchung vertrauenskompensierender Variablen, sondern darum, die Wirkung der Datensammlung auf das Konsumentenvertrauen und letztlich die Kundenbindung zu beleuchten. Pricingthemen stellen jedoch insbesondere in Verbindung mit dem Konsumentenvertrauen und im E-Commerce ein wichtiges Forschungsthema für weitere Arbeiten dar.

Trotz dieser Einschränkungen liefert die vorgelegte Studie einen wesentlichen Grundstein für ein genaueres Verständnis hinsichtlich der Wirkketten zwischen wahrgenommenem Datenzugriffsrisiko und Kundenbindung sowie der Ehrlichkeit des Unternehmens und Kundenbindung.

Literaturverzeichnis

Amazon.de (2018a): Amazon.de Datenschutzerklärung. Online verfügbar unter https://www.amazon.de/gp/help/customer/display.html?nodeId=3312401, zuletzt aktualisiert am 22.05.2018, zuletzt geprüft am 08.08.2018.

Amazon.de (2018b): Cookies. Online verfügbar unter https://www.amazon.de/gp/help/customer/display.html/?nodeId=201890250, zuletzt aktualisiert am 23.05.2018, zuletzt geprüft am 08.08.2018.

Amazon.de (2018c): Datenauskunft über Kevin Seibel nach dem Auskunftsrecht der DSGVO.

Bakos, Yannis; Marotta-Wurgler, Florencia; Trossen, David R. (2014): Does anyone read the fine print? Consumer attention to standard-form contracts. In: *The Journal of Legal Studies* 43 (1), S. 1–35. DOI: 10.1086/674424.

Bapna, Ravi; Gupta, Alok; Rice, Sarah; Sundararajan, Arun (2017): Trust and the strength of ties in online social networks. An exploratory field experiment. In: *MISQ* 41 (1), S. 115–130. DOI: 10.25300/MISQ/2017/41.1.06.

Bauer, Hans H.; Neumann, Marcus M.; Schüle, Anja (Hg.) (2006): Konsumentenvertrauen. Konzepte und Anwendungen für ein nachhaltiges Kundenbindungsmanagement. Unter Mitarbeit von Hans H. Bauer. München: Vahlen.

Bélanger, France; Crossler, Robert E. (2011): Privacy in the Digital Age. A review of Information privacy research in information systems. In: *MISQ* 35 (4), S. 1017–1041. DOI: 10.2307/41409971.

Bhattacherjee, Anol (2002): Individual trust in online firms. Scale development and initial test. In: *Journal of Management Information Systems* 19 (1), S. 211–241. DOI: 10.1080/07421222.2002.11045715.

Bialek, Catrin (2018): Jeder dritte Facebook-Nutzer will seine Aktivitäten einschränken. Datenskandal. Hg. v. Handelsblatt. Online verfügbar unter http://www.handelsblatt.com/unternehmen/it-medien/datenskandal-jeder-dritte-facebook-nutzer-will-seine-aktivitaeten-einschraenken/21164536.html, zuletzt aktualisiert am 12.04.2018, zuletzt geprüft am 01.06.2018.

Bitkom (2016): Bitkom Studie. Datenschutzverordnung & Privacy Shield. Hg. v. Bitkom. Online verfügbar unter https://www.bitkom.org/noindex/Publikationen/2016/Studien/Big-Data-Studie/Studie-Datenschutzgrundverordnung.pdf, zuletzt geprüft am 11.07.2018.

Bitkom (2017): Shopping digital – Wie die Digitalisierung den Handel tiefgreifend verändert. Ein Bitkom-Studienbericht. Hg. v. Bitkom. Online verfügbar unter https://www.bitkom.org/noindex/Publikationen/2017/Studien/2017/171124-Studienbericht-Handel-Web.pdf, zuletzt geprüft am 12.07.2018.

Bloching, Björn; Luck, Lars; Ramge, Thomas (2012): Data Unser. Wie Kundendaten die Wirtschaft revolutionieren. München: Redline.

Brickau, Ralf A.; Städter, Christian (2011): Vertrauensmanagement in Unternehmen. Eine theoretische und empirische Nutzenanalyse unter besonderer Berücksichtigung der Wechselwirkung von Mitarbeiter- und Kundenloyalität. Münster: Monsenstein und Vannerdat (ISM-Schriftenreihe, Bd 17).

Bruhn, Manfred (2016): Relationship Marketing. Das Management von Kundenbeziehungen. München: Verlag Franz Vahlen (Vahlens Handbücher). Online verfügbar unter http://lib.myilibrary.com/detail.asp?ID=904223.

Bruhn, Manfred (2018): Marketing Weiterdenken in der marktorientierten Unternehmensführung – Entwicklungen und Zukunftsthemen der Marketingdisziplin. In: Manfred Bruhn und Manfred

Kirchgeorg (Hg.): Marketing Weiterdenken. Zukunftspfade für eine marktorientierte Unternehmensführung. Unter Mitarbeit von Heribert Meffert. Wiesbaden: Springer Gabler, S. 25–47.

Bruhn, Manfred; Homburg, Christian (Hg.) (2017): Handbuch Kundenbindungsmanagement. Strategien und Instrumente für ein erfolgreiches CRM. 9., überarbeitete Auflage. Wiesbaden: Springer Gabler.

Clarke, Roger (1999): Internet privacy concerns confirm the case for intervention. In: *Commun. ACM* 42 (2), S. 60–67. DOI: 10.1145/293411.293475.

Clemons, Eric K. (2007): An empirical investigation of third-party seller rating systems in E-Commerce. The Case of buySAFE. In: *Journal of Management Information Systems* 24 (2), S. 43–71. DOI: 10.2753/MIS0742-1222240203.

Clemons, Eric K.; Wilson, Josh; Matt, Christian; Hess, Thomas; Ren, Fei; Jin, Fujie; Koh, Noi Sian (2016): Global differences in online shopping behavior. Understanding factors leading to trust. In: *Journal of Management Information Systems* 33 (4), S. 1117–1148. DOI: 10.1080/07421222.2016.1267531.

Das Europäische Parlament; Der Rat der Europäischen Union (2018a): Datenschutz-Grundverordnung. Die Europäische Union. Online verfügbar unter https://eur-lex.europa.eu/legal-content/DE/TXT/PDF/?uri=CELEX:32016R0679&from=DE, zuletzt geprüft am 25.06.2018.

Das Europäische Parlament; Der Rat der Europäischen Union (2018b): Datenschutz-Grundverordnung. Die Europäische Union. Online verfügbar unter https://eur-lex.europa.eu/legal-content/DE/TXT/PDF/?uri=CELEX:32016R0679&from=DE, zuletzt geprüft am 25.06.2018.

Der Bundestag; Der Bundesrat (2018): Gesetz zur Anpassung des Datenschutzrechts. Online verfügbar unter https://www.bmi.bund.de/SharedDocs/downloads/DE/gesetztestexte/datenschutzanpassungsumsetzungsgesetz.pdf?__blob=publicationFile&v=1, zuletzt geprüft am 25.06.2018.

Deutscher Marketing Verband e.V. (2018): Zahl des Monats. In: *absatzwirtschaft* 60 (6), S. 8.

Dunbar, Robin I.M. (2004): Gossip in evolutionary perspective. In: *Review of General Psychology* 8 (2), S. 100–110. DOI: 10.1037/1089-2680.8.2.100.

Ebert, Tara A. E. (2007): Interdisciplinary trust meta-analysis. Analysis of high rank trust articles between 1966 and 2006. In: *Discussion Papers in Business Administration of the Ludwig-Maximilians-Universität München, Munich School of Management* (1).

Eling, Nicole (2017): Der Wert von Nutzerinformationen aus Anbieter- und Nutzerperspektive. Dissertation. Online verfügbar unter http://dx.doi.org/10.1007/978-3-658-19546-5.

Esch, Franz-Rudolf; Ruterberg, Jan (2006): Komplexitätsreduktion durch Vertrauen - kognitive Entlastung für Konsumenten. In: Hans H. Bauer, Marcus M. Neumann und Anja Schüle (Hg.): Konsumentenvertrauen. Konzepte und Anwendungen für ein nachhaltiges Kundenbindungsmanagement. Unter Mitarbeit von Hans H. Bauer. München: Vahlen, S. 193–205.

Feinberg, Matthew; Willer, Robb; Stellar, Jennifer; Keltner, Dacher (2012): The Virtues of gossip. Reputational information sharing as prosocial behavior. In: *Journal of Personality and Social Psychology* 102 (5), S. 1015–1030. DOI: 10.1037/a0026650.

Felser, Georg (2015): Werbe- und Konsumentenpsychologie. 4. erw. und vollst. überarb. Aufl. 2015. Berlin: Springer. Online verfügbar unter http://dx.doi.org/10.1007/978-3-642-37645-0.

Foster, Eric K. (2004): Research on gossip. Taxonomy, methods, and future directions. In: *Review of General Psychology* 8 (2), S. 78–99.

Fournier, Susan (1998): Consumers and their brands. Developing relationship theory in consumer research. In: *J CONSUM RES* 24 (4), S. 343–353. DOI: 10.1086/209515.

Foxman, Ellen R.; Kilcoyne, Paula (1993): Information technology, Marketing practice, and consumer privacy. Ethical Issues. In: *Journal of Public Policy & Marketing* 12 (1), S. 106–119.

Friedewald, Michael (2018): Einleitung: Privatheit und selbstbestimmtes Leben in der Digitalen Welt. In: Michael Friedewald (Hg.): Privatheit und selbstbestimmtes Leben in der digitalen Welt. Interdisziplinäre Perspektiven auf aktuelle Herausforderungen des Datenschutzes. Wiesbaden: Springer Vieweg (DuD-Fachbeiträge).

Gefen, David; Benbasat, Izak; Pavlou, Paul A. (2008): A research agenda for trust in online environments. In: *Journal of Management Information Systems* 24 (4), S. 275–286.

Georgi, Dominik (2010): Kundenbindungsmanagement im Kundenbeziehungslebenszyklus. In: Manfred Bruhn (Hg.): Handbuch Kundenbindungsmanagement. 7., vollst. überarb. und aktualisierte Aufl. Wiesbaden: Gabler, S. 277–298.

Gerrig, Richard J.; Zimbardo, Philip G. (2015): Psychologie. Unter Mitarbeit von Andreas Klatt, Tobias Dörfler und Jeanette Roos. 20., aktualisierte Auflage. Hallbergmoos: Pearson (Always Learning). Online verfügbar unter http://lib.myilibrary.com?id=651020.

Giering, Annette (2000): Der Zusammenhang zwischen Kundenzufriedenheit und Kundenloyalität. Eine Untersuchung moderierender Effekte. Zugl.: Mannheim, Univ., Diss., 2000. Wiesbaden: Dt. Univ.-Verl. (Gabler-Edition Wissenschaft Schriftenreihe des Instituts für Marktorientierte Unternehmensführung (IMU), Universität Mannheim).

Gierl, Herbiert (2006): Vertrauen als Heuristik. In: Hans H. Bauer, Marcus M. Neumann und Anja Schüle (Hg.): Konsumentenvertrauen. Konzepte und Anwendungen für ein nachhaltiges Kundenbindungsmanagement. Unter Mitarbeit von Hans H. Bauer. München: Vahlen, S. 135–149.

Gondorf, Linda (2018): Die maximale Entschuldigung. In: *absatzwirtschaft* (5), S. 26–27.

Grabner-Kräuter, Sonja; Fladnitzer, Marliese (2006): Perspektiven von Konsumentenvertrauen im Internet. In: Hans H. Bauer, Marcus M. Neumann und Anja Schüle (Hg.): Konsumentenvertrauen. Konzepte und Anwendungen für ein nachhaltiges Kundenbindungsmanagement. Unter Mitarbeit von Hans H. Bauer. München: Vahlen, S. 367–378.

Grohmann, Marcella; Heumann, Christian; von Wagenheim, Florian (2017): Determinanten der Kundenbindung. In: Manfred Bruhn und Christian Homburg (Hg.): Handbuch Kundenbindungsmanagement. Strategien und Instrumente für ein erfolgreiches CRM. 9., überarbeitete Auflage. Wiesbaden: Springer Gabler.

Gröppel-Klein, Andrea; Königstorfer, Jörg; Terlutter, Ralf (2017): Verhaltenswissenschaftliche Aspekte der Kundenbindung. In: Manfred Bruhn und Christian Homburg (Hg.): Handbuch Kundenbindungsmanagement. Strategien und Instrumente für ein erfolgreiches CRM. 9., überarbeitete Auflage. Wiesbaden: Springer Gabler, S. 37–75.

Hoffman, Donna L.; Novak, Thomas P.; Peralta, Marcos (1999): Building consumer trust online. In: *Commun. ACM* 42 (4), S. 80–85. DOI: 10.1145/299157.299175.

Hoffmann, Christian Pieter; Lutz, Christoph; Meckel, Miriam (2014): Digital Natives or Digital Immigrants? The impact of user characteristics on online trust. In: *Journal of Management Information Systems* 31 (3), S. 138–171. DOI: 10.1080/07421222.2014.995538.

Holzmüller, Hartmut H.; Hessenkamp, Vanessa; Wilke, Claus (2006): Das Vertrauen von Konsumenten in eine Branche - Konzeptualisierung und Operationalisierung. In: Hans H. Bauer, Marcus M. Neumann und Anja Schüle (Hg.): Konsumentenvertrauen. Konzepte und Anwendungen für ein nachhaltiges Kundenbindungsmanagement. Unter Mitarbeit von Hans H. Bauer. München: Vahlen, S. 409–423.

Homburg, Christian; Bruhn, Manfred (2017): Kundenbindungsmanagement - Eine Einführung in die theoretischen und praktischen Problemstellungen. In: Manfred Bruhn und Christian Homburg (Hg.): Handbuch Kundenbindungsmanagement. Strategien und Instrumente für ein erfolgreiches CRM. 9., überarbeitete Auflage. Wiesbaden: Springer Gabler, S. 3–39.

Homburg, Christian; Stock-Homburg, Ruth (2016): Theoretische Perspektiven zur Kundenzufriedenheit. In: Christian Homburg (Hg.): Kundenzufriedenheit. Konzepte - Methoden - Erfahrungen. 9., überarbeitete Auflage. Wiesbaden: Springer Gabler, S. 17–52.

idealo (2018): E-Commerce Trends 2018. Wünsche und Ängste von Online-Shoppern. Hg. v. idealo. Online verfügbar unter https://www.idealo.de/unternehmen/wp-content/uploads/sites/33/2018/02/2018-01-23_E-Commerce-Trends-2018_Wuensche-und-Aengste-von-Online-Shoppern.pdf, zuletzt geprüft am 03.07.2018.

Joiner, Richard; Gavin, Jeff; Brosnan, Mark; Cromby, John; Gregory, Helen; Guiller, Jane et al. (2013): Comparing first and second generation Digital Natives' Internet use, Internet anxiety, and Internet identification. In: *Cyberpsychology, Behavior and Social Networking* 16 (7), S. 549–552. DOI: 10.1089/cyber.2012.0526.

Kenning, Peter; Blut, Markus (2006): Vertrauen: Ein Objekt des Marketingmanagements?! In: Hans H. Bauer, Marcus M. Neumann und Anja Schüle (Hg.): Konsumentenvertrauen. Konzepte und Anwendungen für ein nachhaltiges Kundenbindungsmanagement. Unter Mitarbeit von Hans H. Bauer. München: Vahlen, S. 3–15.

Kollmann, Tobias (2013): E-Business. Grundlagen elektronischer Geschäftsprozesse in der Net Economy. 5., überarb. und erw. Aufl. Wiesbaden: Springer Gabler (Lehrbuch).

Kuipers, Benjamin (2018): How can we trust a robot? In: *Commun. ACM* 61 (3), S. 86–95. DOI: 10.1145/3173087.

Lewis, J. David; Weigert, Andrew (1985): Trust as a social reality. In: *Social Forces* 63 (4), S. 967–985. DOI: 10.2307/2578601.

Malhotra, Naresh K.; Kim, Sung S.; Agarwal, James (2004): Internet users' Information Privacy Concerns (IUIPC). The construct, the scale, and a causal Model. In: *Information Systems Research* 15 (4), S. 336–355. DOI: 10.1287/isre.1040.0032.

Martin, Kelly D.; Borah, Abhishek; Palmatier, Robert W. (2017): Data privacy. Effects on customer and firm performance. In: *Journal of Marketing* 81 (1), S. 36–58. DOI: 10.1509/jm.15.0497.

Martin, Kelly D.; Murphy, Patrick E. (2017): The role of data privacy in Marketing. In: *J. of the Acad. Mark. Sci.* 45 (2), S. 135–155. DOI: 10.1007/s11747-016-0495-4.

Martin, Kirsten (2013): Transaction costs, privacy, and trust. The laudable goals and ultimate failure of notice and choice to respect privacy online. In: *FM* 18 (12). DOI: 10.5210/fm.v18i12.4838.

McAllister, Daniel J. (1995): Affect- and cognition-based trust as foundations for interpersonal cooperation in organizations. In: *AMJ* 38 (1), S. 24–59. DOI: 10.2307/256727.

McDonald, Aleecia M.; Cranor, Lorrie Faith (2008): The cost of reading privacy policies. In: *I/S: A Journal of Law and Policy for the Information Society* 4 (3), S. 543–568.

McKnight, D. Harrison; Choudhury, Vivek; Kacmar, Charles (2002): Developing and validating trust measures for E-Commerce. An integrative typology. In: *Information Systems Research* 13 (3), S. 334–359. DOI: 10.1287/isre.13.3.334.81.

Menon, Syam; Sarkar, Sumit (2016): Privacy and Big Data. Scalable approaches to sanitize large transactional databases for sharing. In: *MISQ* 40 (4), S. 963–981. DOI: 10.25300/MISQ/2016/40.4.08.

Mertens, Peter; Bodendorf, Freimut; König, Wolfgang; Schumann, Matthias; Hess, Thomas; Buxmann, Peter (2017): Grundzüge der Wirtschaftsinformatik. 12., grundlegend überarbeitete Auflage. Berlin: Springer Gabler. Online verfügbar unter http://dx.doi.org/10.1007/978-3-662-53362-8.

Meyer, A.; Oevermann, D. (1995): Kundenbindung. In: Bruno Tietz, Richard Köhler und Joachim Zentes (Hg.): Handwörterbuch des Marketing. 2., völlig neu gestaltete Aufl. Stuttgart: Schäffer-Poeschel (Enzyklopädie der Betriebswirtschaftslehre, Bd. 4), S. 1340–1351.

Milne, George R.; Bahl, Shalini (2010): Are there differences between consumers' and Marketers' privacy expectations? A segment- and technology-level analysis. In: *Journal of Public Policy & Marketing* 29 (1), S. 138–149. DOI: 10.1509/jppm.29.1.138.

Miyazaki, Anthony D. (2008): Online privacy and the disclosure of Cookie use. Effects on consumer trust and anticipated patronage. In: *Journal of Public Policy & Marketing* 27 (1), S. 19–33. DOI: 10.1509/jppm.27.1.19.

Morey, Timothy; Forbath, Theodore; Schoop, Allison (2015): Customer data. Designing for transparency and trust. In: *Harvard Business Review* (4), S. 96–105. Online verfügbar unter https://hbr.org/2015/05/customer-data-designing-for-transparency-and-trust, zuletzt geprüft am 17.05.2018.

Morlok, Tina; Matt, Christian; Hess, Thomas (2018): Perspektiven der Privatheitsforschung in den Wirtschaftswissenschaften. Konsumentenkalkül im Neuen Kontext und Datenmärkte. In: Michael Friedewald (Hg.): Privatheit und selbstbestimmtes Leben in der digitalen Welt. Interdisziplinäre Perspektiven auf aktuelle Herausforderungen des Datenschutzes. Wiesbaden: Springer Vieweg (DuD-Fachbeiträge), S. 179–220.

Müller, Oliver; Fay, Maria; vom Brocke, Jan (2018): The effect of Big Data and analytics on firm performance. An econometric analysis considering industry characteristics. In: *Journal of Management Information Systems* 35 (2), S. 488–509. DOI: 10.1080/07421222.2018.1451955.

Müller-Hagedorn, Lothar; Preißner, Marcus; Wilke, Kai (2006): Die Rolle des Vertrauens bei der Beurteilung der Preisgünstigkeit. In: Hans H. Bauer, Marcus M. Neumann und Anja Schüle (Hg.): Konsumentenvertrauen. Konzepte und Anwendungen für ein nachhaltiges Kundenbindungsmanagement. Unter Mitarbeit von Hans H. Bauer. München: Vahlen, S. 151–165.

Nerdinger, Friedemann W.; Neumann, Christina; Curth, Susanne (2015): Kundenzufriedenheit und Kundenbindung. In: Klaus Moser (Hg.): Wirtschaftspsychologie. 2., vollst. überarb. und aktual. Aufl. 2015. Berlin: Springer (Springer-Lehrbuch), S. 119–138.

Neumann, Marcus M. (2007): Konsumentenvertrauen. Messung, Determinanten und Konsequenzen. Zugl.: Mannheim, Univ., Diss., 2006. Wiesbaden: Dt. Univ.-Verl. (Gabler-Edition Wissenschaft Schriftenreihe des Instituts für Marktorientierte Unternehmensführung (IMU), Universität Mannheim).

Noll, Jürgen; Winkler, Michaela (2004): Gütesiegel und Vertrauen im E-Commerce. In: *Journal für Marketing* 43 (1), S. 23–32. DOI: 10.1007/BF03032266.

Nooteboom, Bart (2002): Trust. Forms, foundations, functions, failures and figures. Cheltenham: Edward Elgar.

Palfrey, John (2007): Born digital. Phillips Academy. Online verfügbar unter https://jpalfrey.andover.edu/2007/10/28/born-digital/, zuletzt aktualisiert am 28.10.2007, zuletzt geprüft am 26.06.2018.

Palfrey, John; Gasser, Urs (2008): Born digital. Understanding the first generation of Digital Natives. New York: Basic Books. Online verfügbar unter http://site.ebrary.com/lib/academiccompletetitles/home.action.

Petermann, Franz (2013): Psychologie des Vertrauens. 4., überarb. Aufl. Göttingen: Hogrefe.

Petermann, Franz; Winkel, Sandra (2006): Interpersonelles Vertrauen - Grundlagen, Messung, empirische Befunde. In: Hans H. Bauer, Marcus M. Neumann und Anja Schüle (Hg.): Konsumentenvertrauen. Konzepte und Anwendungen für ein nachhaltiges Kundenbindungsmanagement. Unter Mitarbeit von Hans H. Bauer. München: Vahlen, S. 77–91.

Prensky, Marc (2001a): Digital Natives, Digital Immigrants. In: *On The Horizon* 9 (5), S. 1–6. DOI: 10.1108/10748120110424816.

Prensky, Marc (2001b): Digital Natives, Digital Immigrants part 2. Do they really think differently? In: *On The Horizon* 9 (6), S. 1–6. DOI: 10.1108/10748120110424843.

Puscher, Frank (2018): Noch 120 Tage Panik. In: *absatzwirtschaft* (1/2), S. 26–39.

Rempel, John K.; Holmes, John G.; Zanna, Mark P. (1985): Trust in close relationships. In: *Journal of Personality and Social Psychology* 49 (1), S. 95–112. DOI: 10.1037//0022-3514.49.1.95.

Rice, Sarah C. (2012): Reputation and uncertainty in online markets. An experimental study. In: *Information Systems Research* 23 (2), S. 436–452. DOI: 10.1287/isre.1110.0362.

Rotter, Julian B. (1971): Generalized expectancies for interpersonal trust. In: *American Psychologist* 26 (5), S. 443–452. DOI: 10.1037/h0031464.

Scharf, S. (2007): Report casts doubt on the impact of data breaches on identity theft. In: *Internal Auditor* 64 (4), S. 23.

Schlosser, Ann E.; White, Tiffany Barnett; Lloyd, Susan M. (2006): Converting web site visitors into buyers. How web site investment increases consumer trusting beliefs and online purchase intentions. In: *Journal of Marketing* 70 (2), S. 133–148. DOI: 10.1509/jmkg.70.2.133.

Schubach, Sebastian; Garbas, Janina; Schumann, Jan Hendrik (2017): Kundenbindung im digitalen Zeitalter. In: Manfred Bruhn und Christian Homburg (Hg.): Handbuch Kundenbindungsmanagement. Strategien und Instrumente für ein erfolgreiches CRM. 9., überarbeitete Auflage. Wiesbaden: Springer Gabler, S. 301–331.

Sidgman, Juergen; Crompton, Malcolm (2016): Valuing personal data to foster privacy. A thought experiment and opportunities for research. In: *Journal of Information Systems* 30 (2), S. 169–181. DOI: 10.2308/isys-51429.

Sirdeshmukh, Deepak; Singh, Jagdip; Sabol, Barry (2002): Consumer trust, value, and loyalty in relational exchanges. In: *Journal of Marketing* 66 (1), S. 15–37. DOI: 10.1509/jmkg.66.1.15.18449.

Sirohi, Niren; McLaughlin, Edward W.; Wittink, Dick R. (1998): A model of consumer perceptions and store loyalty intentions for a supermarket retailer. In: *Journal of Retailing* 74 (2), S. 223–245.

Smith, H. Jeff; Dinev, Tamara; Xu, Heng (2011): Information privacy research. An interdisciplinary review. In: *MISQ* 35 (4), S. 989–1015. DOI: 10.2307/41409970.

Stephan, Birgit; Werther, Simon (2013): Der Konsument 2.0. In: Erika Spieß (Hg.): Konsumentenpsychologie. München: Oldenbourg, S. 125–136.

Stüber, Eva; Leyendecker, Carolin; Heinick, Hansjürgen (2019): Gatekeeper Amazon. Vom Suchen und Finden des eigenen Erfolgswegs. Hg. v. IFH Köln.

Tang, Zhulei; Hu, Yu; Smith, Michael D. (2008): Gaining trust through online privacy protection. Self-regulation, mandatory standards, or caveat emptor. In: *Journal of Management Information Systems* 24 (4), S. 153–173. DOI: 10.2753/MIS0742-1222240406.

Tasselli, Stefano; Kilduff, Martin (2018): When brokerage between friendship cliques endangers trust. A personality–network fit perspective. In: *AMJ* 61 (3), S. 802–825. DOI: 10.5465/amj.2015.0856.

Tirunillai, Seshadri; Tellis, Gerard J. (2014): Mining Marketing meaning from online chatter. Strategic brand analysis of Big Data using latent dirichlet allocation. In: *Journal of Marketing Research* 51 (4), S. 463–479. DOI: 10.1509/jmr.12.0106.

Turner, Monique Mitchell; Mazur, Michelle A.; Wendel, Nicole; Winslow, Robert (2003): Relational ruin or social glue? The joint effect of relationship type and gossip valence on liking, trust, and expertise. In: *Communication Monographs* 70 (2), S. 129–141. DOI: 10.1080/0363775032000133782.

Urban, Glen L.; Amyx, Cinda; Lorenzon, Antonio (2009): Online trust. State of the art, new frontiers, and research potential. In: *Journal of Interactive Marketing* 23 (2), S. 179–190. DOI: 10.1016/j.intmar.2009.03.001.

Vanhala, Mika; Ritala, Paavo (2016): HRM practices, impersonal trust and organizational innovativeness. In: *Journal of Managerial Psych* 31 (1), S. 95–109. DOI: 10.1108/JMP-03-2013-0084.

Vodanovich, Shahper; Sundaram, David; Myers, Michael (2010): Digital Natives and ubiquitous information systems. In: *Information Systems Research* 21 (4), S. 711–723. DOI: 10.1287/isre.1100.0324.

Wedel, Michel; Kannan, P. K. (2016): Marketing Analytics for data-rich environments. In: *Journal of Marketing* 80 (6), S. 97–121. DOI: 10.1509/jm.15.0413.

Weiber, Rolf; Egner-Duppich, Christel (2006): Vertrauen bei Online-Käufen. Ein transaktionsbezogener Ansatz aus informationsökonomischer Sicht. In: Hans H. Bauer, Marcus M. Neumann und Anja Schüle (Hg.): Konsumentenvertrauen. Konzepte und Anwendungen für ein nachhaltiges Kundenbindungsmanagement. Unter Mitarbeit von Hans H. Bauer. München: Vahlen, S. 341–354.

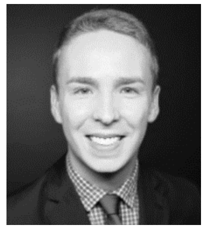
White, Tiffany Barnett; Yuan, Hong (2012): Building trust to increase purchase intentions. The signaling impact of low pricing policies. In: *Journal of Consumer Psychology* 22 (3), S. 384–394. DOI: 10.1016/j.jcps.2011.09.003.

Zeithaml, Valarie A.; Berry, Leonard L.; Parasuraman, A. (1996): The behavioral consequences of service quality. In: *Journal of Marketing* 60 (2), S. 31–46. DOI: 10.2307/1251929.

Zentes, Joachim; Morschett, Dirk; Schramm-Klein, Hanna (2006): Konsumentenvertrauen im Handel - Bedeutung und Einflussfaktoren. In: Hans H. Bauer, Marcus M. Neumann und Anja Schüle (Hg.): Konsumentenvertrauen. Konzepte und Anwendungen für ein nachhaltiges Kundenbindungsmanagement. Unter Mitarbeit von Hans H. Bauer. München: Vahlen, S. 393–405.

Zhang, Tongxiao; Agarwal, Ritu; Lucas, Henry C. (2011): The value of IT-enabled retailer learning. Personalized product recommendations and customer store loyalty in electronic markets. In: *MISQ* 35 (4), S. 859–881. DOI: 10.2307/41409964.

Autoren



Kevin **Seibel** studierte Wirtschaftspsychologie an der International School of Management in Frankfurt. Im Studium spezialisierte er sich auf die Markt-, Werbe- und Konsumentenpsychologie. Während des Studiums absolvierte Kevin Seibel diverse Praktika in den Bereichen Unternehmensstrategie, Marketing und Public Relations. Zudem arbeitete er als Werkstudent in einer Beratung für strategische Unternehmenskommunikation. Seit 2019 arbeitet er als Unternehmensberater für Strategie und Marketing in Frankfurt und fokussiert sich hierbei auf die internationale Konsumgüter- und Handelsindustrie.

Prof. Dr. Stephan **Bingemer** studierte Wirtschaftsingenieurwesen mit technischer Fachrichtung Elektrotechnik und Informationstechnik an der TU Darmstadt und promovierte am Lehrstuhl für Business-to-Business Marketing, Sales & Pricing (Prof. Dr. Dr. h.c. mult. Christian Homburg) an der Universität Mannheim. Zwischen 2008 und 2017 war er bei der Deutschen Lufthansa AG in verschiedenen Vertriebs- und Managementpositionen beschäftigt, zuletzt als Head of Distribution Solutions. Von Oktober 2017 bis März 2020 war Bingemer Professor für allgemeine Betriebswirtschaftslehre und Tourismus an der International School of Management, Campus Frankfurt. Seit 2020 ist er Professor für Travel Technology & E-Business an der Fakultät International Business der Hochschule Heilbronn.

Prof. Dr. Jens **Brandt** studierte Psychologie an der Universität Würzburg und promovierte an der Universität Graz. Seit 1999 ist er in der angewandten psychologischen Forschung und Beratung tätig. Seit 2013 ist er Professor für Wirtschaftspsychologie an der International School of Management in Frankfurt.

CALL FOR PAPERS - RESEARCH JOURNAL FOR APPLIED MANAGEMENT 2022

Das Research Journal for Applied Management (RJAM) ist eine Fachzeitschrift für neue Trends und Strömungen in den praxis-relevanten Managementbereichen Internationalisierung der Wirtschaft, ressourcenökonomische Forschung, Tourismusforschung, Logistik- und Informationsforschung, Finanz- und Bankenforschung, Marketing- und Kommunikationsforschung, Immobilienforschung, Leadership- und Motivationsforschung und Organisations- und Personalforschung. Das Research Journal for Applied Management versteht sich als eine praxisrelevante und transdisziplinäre Fachzeitschrift für Fragen und kritische Analysen von wirtschaftlichen, sozialen und politischen Veränderungen, insbesondere von Systemen, aber auch von interorganisationalen Prozessen.

Ziel des **Research Journal for Applied Management** ist es, die jeweils aktuellen Entwicklungen und Ergebnisse der Forschung zu den Fragen der praxisrelevanten Managementbereiche aufzuzeigen und fortzuentwickeln. Das Research Journal for Applied Management steht für alle Wissenschaftlerinnen und Wissenschaftler offen, die Management als Funktion, Institution oder Praktik untersuchen. Im Focus der Artikel soll die Erarbeitung neuer Perspektiven oder die Erschließung innovativer Problemstellungen stehen. Willkommen sind sowohl empirische Studien, konzeptionelle Analysen als auch anwendungsorientierte Studien. Weitere Informationen zum Research Journal for Applied Management sind hier verfügbar: https://www.ism.de/forschung/forschungsaktivitaeten.

Die Einreichung von Beiträgen ist jederzeit möglich. Im Beitrag sind die verwendeten Zitate (direkte, indirekte) mit Seitenzahl anzugeben. Zur Begutachtung angenommene Beiträge durchlaufen ein Double Blind Peer Review Begutachtungsverfahren nach internationalen Standards – mit mindestens zwei Fachgutachterinnen bzw. Fachgutachtern. Die Publikationssprachen sind Deutsch und Englisch. Zur Erleichterung unserer Disposition bitten wir darum, geplante Beiträge möglichst frühzeitig einzureichen. Die maximale Länge des gesamten Beitrags liegt bei ca. 20 Seiten einschließlich eines Abstracts im Umfang von max. 250 Wörtern. Einreichungen können als Word-Dokument per E-Mail an robinson.nittke@ism.de geschickt werden.

Bitte erstellen Sie zusätzlich Ihre Abbildungen in Microsoft PowerPoint und reichen die entsprechende Datei separat ein. Über eine Eignung des Beitrags entscheidet das Editorial Board zeitnah. Bitte beachten Sie unbedingt den Guide mit Formatvorlage https://www.ism.de/images/downloads/style-sheet-deutsch.pdf. Die Beiträge sollen grundsätzlich das generische Maskulinum verwenden. Abweichende Geschlechterformulierungen müssen den Anforderungen an die deutsche Rechtschreibung gemäß Duden entsprechen und konsistent angewendet werden. Die Literatur sollte als Projekt (Citavi oder ähnliches) zur Verfügung gestellt werden, um den redaktionellen Prozess zu erleichtern.

Artikel zu Themen aller Managementbereiche sind willkommen.

Kontakt

International School of Management (ISM)
Vizepräsident für Forschung
Otto-Hahn-Straße 19 · 44227 Dortmund
E-Mail: kai.rommel@ism.de, robinson.nittke@ism.de
https://www.ism.de/
https://www.ism.de/forschung/forschungsaktivitaeten

CALL FOR PAPERS - RESEARCH JOURNAL FOR APPLIED MANAGEMENT 2021

The Research Journal for Applied Management (RJAM) is a specialized journal for new trends and directions in practice-relevant management topics focusing on the internationalization of the economy, resource economics, tourism, logistics and information sciences, finance and banking research, marketing and communication research, real estate, leadership and motivational research and organization, and human resource research. The RJAM itself is a practice-oriented and trans-disciplinary journal for questions and critical analyses addressing economic, social and political change, in particular regarding systems, but also for intercorporate processes.

The RJAM aims to show trends and developments in current studies and further elaborate on questions which arise regarding practice-oriented management fields. The RJAM serves as a platform for all scientists, who intend to publish research in the field of management. Articles published in the RJAM assess management in terms of its function, its methodologies and examine the institutions behind it.

Articles should be focused on elaborating upon new perspectives or an innovative presentation of a problem. Empirical studies, conceptual analysis and application oriented studies are always welcome. More information on the Research Journal for Applied Management are available here: https://en.ism.de/research/research-activities.

It is generally possible to submit articles at any point of time. The article can be submitted in English or German to robinson.nittke@ism.de. The article has to be submitted according to the provided guidelines and style sheet (https://www.ism.de/images/downloads/style-sheet-research-journal.pdf). The maximum size of submitted papers is around 20 pages including an abstract with not more than 250 words. Submissions should use the non-gender specific pronouns e.g. ‘they” or ‘it’. Any alternative form of gender formulation must be used consistently and according to English grammar Please note, authors are strongly requested to create their figures in Microsoft PowerPoint and to submit the corresponding file separately. Regarding quotes used in the article (direct and indirect ones) page numbers have to be specified. Articles accepted for review will undergo a double blind peer review process in accordance with international standards – the peer review will be conducted by at least two referees.

In addition to the article and abstract itself, authors are asked to submit their references in form of a Citavi project (other reference management programs can be accepted after consultation with the editors).
The editors adhere to decide upon qualification in a timely manner.

Articles concerning all types of management fields are welcome.

Contact:
International School of Management (ISM)
Vice President Research
Otto-Hahn-Str. 19 · 44227 Dortmund
e-mail: kai.rommel@ism.de, robinson.nittke@ism.de
https://en.ism.de/
https://en.ism.de/research/research-activities