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Master-Arbeit zur Erlangung des akademischen Grades
eines Master of Science (Wirtschaftsinformatik)
Julius-Maximilians-Universität Würzburg

BlaBlaCar – Business Model and Empirical Analysis of Usage Patterns

Eingereicht bei:	Professor Toker Doganoglu, Ph.D.
	Lehrstuhl für VWL, insbesondere Industrieökonomik
	Julius-Maximilians-Universität Würzburg
Betreuer:	Professor Toker Doganoglu, Ph.D.
Abgabedatum:	29.09.2017

Erstellt von:	Nico Müller
	Albrecht-Dürer-Str.181
	97204 Höchberg
	Matrikelnummer.: 1758540

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Zusammenfassung

Die vorgelegte Arbeit behandelt das Thema “Sharing Economy” im Allgemeinen und die Mitfahrzentrale BlaBlaCar.de im Speziellen.

“Sharing Economy” gehört zu einem der spannendsten Forschungsfelder der letzten Jahre. Viele klassische Wirtschaftszweige fürchten neue Konkurrenten, Airbnb beispielsweise stellt eine kostengünstigere Alternative zum Hotelgewerbe dar. Mitfahrzentralen wie BlaBlaCar ermöglichen es, gegen einen vergleichbar geringen Betrag zu reisen.

Da die Preise, welche von den Fahrern festgelegt werden, nicht vorgegeben sind, sondern zumindest in einem bestimmten Rahmen flexibel sind, ist es interessant herauszufinden, welche Faktoren diesen Preis beeinflussen. Verlangen beispielsweise erfahrenere Fahrer höhere Preise als Neulinge oder sind Fahrten mit Frauen günstiger als mit Männern?

Außerdem stellt sich die Frage, ob der Preis das Hauptkriterium einer Buchung ist oder welche Faktoren noch eine Rolle spielen.

Zu diesem Zwecke wurden über einen Zeitraum von drei Monaten 272 ausgewählte Strecken untersucht, um sowohl Einflüsse auf den Preis als auch auf die Nachfrage zu untersuchen.

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API	Application Programming Interface
B2P	Business-to-Peer
P2P	Peer-to-Peer
VC	Venture Capital

1 Introduction

1.1 Problem Statement and Ambition

The idea of "sharing economy" is one of the most interesting economical topics in recent years. People share food, apartments and unused seats in their cars. Enabled by web-based services like social networks, the number of users increases every day.

Living hundreds of kilometers away from my home town makes every visit difficult, whether it is a family member's birthday, a football match or Christmas. You can say that there are three options for travelling: by train, fast but very expensive, by bus, very slow but rather cheap or by car, not as fast as by train but cheaper. Nevertheless, it is still costly and travelling alone for hours can also be boring. The solution to this problem is to offer empty seats on carpooling-platforms like BlaBlaCar. BlaBlaCar helps to bring together drivers with empty seats and people who cannot afford travelling by train and do not want to travel by bus. Carpooling combines economical, ecological and social advantages. Drivers can save a lot of money by offering empty seats which is also more environmentally friendly. Finally, chatting makes the drive less boring and one might become acquainted with the car driver.

BlaBlaCar's founder Frédéric Mazzella faced the same dilemma when the idea for his carpooling-network was born: Living in Paris and wanting to visit his family in the French countryside, he wondered why so many people travelled alone and if it was possible to make driving more efficient.

As a user, it is also interesting to know how this platform works: why are some offers more expensive than others, even though the service is the same? From another point of view: why are some offers more popular, ergo the seats in a car are more quickly fully occupied? To answer these questions, this work will deal with the following research question:

Research question:

"What is BlaBlaCar's business model and which parameters affect demand and price of certain trips?"

1.2 Setup

This working paper examines the effect of different parameters on price and demand of different trips in Germany offered on BlaBlaCar.de. For this purpose, an empirical analysis was performed for the period from May to mid-August 2017. Following this section, the reader finds the methodological procedure divided in methods of literature review and data analysis.

The second chapter deals with the topic “Sharing Economy” in general. Therefore, a short definition and popular examples are given.

The following chapter focusses on a sub-aspect of sharing economy – the sharing of cars. To prepare the analysis, the business model of BlaBlaCar will be discussed in this chapter.

In chapter four, the main section of this paper, the data analysis is performed. It shows which variables could affect price and demand and which ones *really* have an effect.

The last chapter sums up the results from the previous chapter and gives an outlook to the future of the sharing economy.

1.3 Research Setting and Methodology

Since the research question consists of two parts, the theoretical part and a rather practical one, the methodology has also to be bipartite. To answer the first part of the research question, a literature review was performed. The second question can only be solved by performing a regression analysis.

1.3.1 Literature Review

To answer the research question mentioned above, a literature review based on a five-stage framework (see figure 1).[1] These five steps are only described briefly, because an exhaustive literature analysis would be beyond the scope.

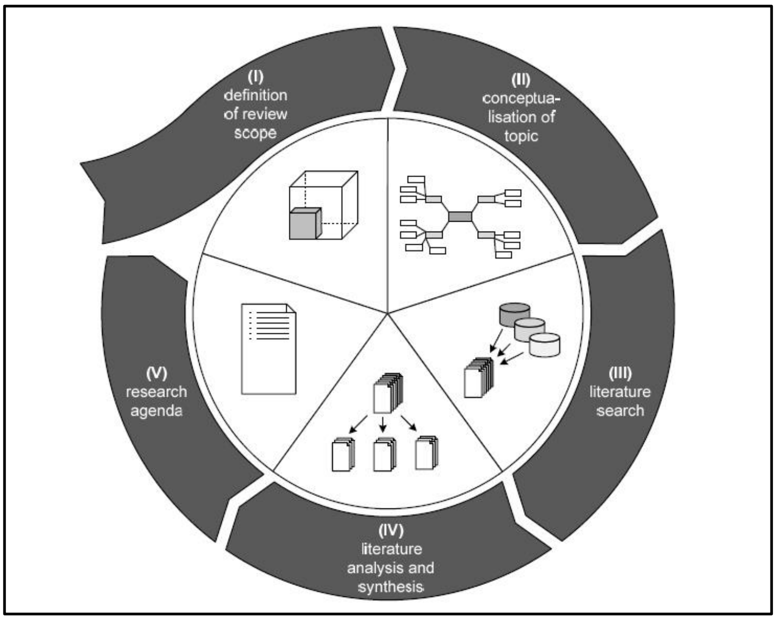

Figure 1: Framework for literature reviewing
(Source: Vom Brocke et al. 2009, p. 2212)

Before starting the actual literature research, the scope (step I) should be defined in order to limit the selection of literature. Cooper[2] defines six different characteristics. The classification of this paper is displayed in table 1.

Table 1: Taxonomy of literature reviews
(Source: based on Cooper 1988, p. 109)

Characteristic	Categories			
1. focus	**research outcomes**	research methods	**theories**	applications
2. goal	integration	criticism		**central issues**
3. organization	historical	**conceptual**		Methodological
4. perspective	**neutral representation**		espousal of position	
5. audience	**specialized scholars**	**general scholars**	practitioners/politicians	**general public**
6. coverage	exhaustive	exhaustive and selective	**representative**	central/pivotal

[1] Cf. Vom Brocke et al. (2009), p. 9.

[2] Cf. Cooper (1988), p. 109.

After setting the criteria and a basic concept of the paper (step II), the next step was searching for relevant articles in the specialist literature (step III). With help of databases like AISeL, ScienceDirect, SpringerLink and Google Scholar, sources with a good degree of quality should be found. The main keywords used in this search were “BlaBlaCar”, “Sharing Economy”, “Airbnb” and “Uber”, which turned out as a misleading keyword, because it can be mixed up with the German word “über”, it is recommended to use in combination with other keywords. The last steps, literature analysis and synthesis (step IV) and a research agenda (step V) were performed afterwards.

1.3.2 Data Analysis

To answer the second part of the research question, a multiple regression was performed. This analysis followed five steps:

1. Preparation
2. Data Collection
3. Clean up Data
4. Perform Analysis
5. Interpretation

In the first step, some questions need to be answered: how will data be collected? Which scope will be used and which period of time will be observed? Which data can be relevant to answer the questions?[3]

For this paper, data was collected automated using BlaBlaCar’s application programming interface (API).[4] Data was scraped from May 2017 to mid-August 2017, at least once a day for 272 selected trips (for detailed information see chapter 4.1 and Appendix A for the original code).

After collecting an amount of 136 datasets with a whole of 9.65 million observations, these datasets had to be cleaned up before the analysis. In order to get the best results, only the latest observation of each trip (distinguishable by a unique trip id) was chosen. Following the cleaning process, the final dataset was reduced to 250,861 unique observations.

[3] Cf. Wooldridge (2008), p.71.

[4] BlaBlaCar’s API only offers a limited access to driver’s information (Cf. BlaBlaCar (2017c)). Thanks to the development team, access was extended for this purpose.

To find out which parameters affect the price and the demand in these observations, a regression analysis with the following model was performed:

$$y = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k + u$$

Where y is the explained variable (price or sold seats respectively), β_0 the intercept, β_1 ... β_k parameters associated with the k independent variables x and the error term u.[5] The independent variables are both named and explained in chapter 4.1. After the regression, the results are discussed in chapter 4.3.

[5] Cf. Wooldridge (2008), p. 71f.

2 “Sharing Economy”

While the idea of sharing is not new, the term “Sharing Economy” is indeed. And its popularity is growing: surveys found that almost one of five adults in the US had experience in sharing economy transactions.[6]

However, this term must not be mixed up with “Gift Economy”. People exchange goods or service with money, but not in a “traditional” way of buying and selling goods.[7] Enabled by digital technologies[8] like smartphones, GPS and payment systems[9] combined with the ubiquity of Internet,[10] people can share almost everything: from selling unused things on platforms like eBay or Craigslist[11]to renting out spare rooms on Airbnb to a vehicle which is not needed or even renting out their pets.[12]

The following chapter will give an overview over different business models inside the sharing economy. Therefore, a focus will be on Airbnb which is one of the most popular examples for sharing rooms or apartments.

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[6] Cf. Wallsten (2015), p. 3.

[7] Cf. Sundararajan (2016), pp. 3ff.

[8] Cf. Ibid., p. 31.

[9] Cf. Wallsten (2015), p. 3.

[10] Cf. Cohen and Kietzmann (2014), p. 279.

[11] Cf. Schor (2016), p. 2.

[12] Cf. Zervas et al. (2014), p. 2.

2.1 Definition/Overview

There is no universal definition of sharing economy. To define a framework, sociologist Juliet Schor divides business models into four categories, namely:

1. Recirculation of Goods
2. Increased Utilization of Durable Assets
3. Exchange of Services
4. Sharing of Productive Assets[13]

Additionally, within these categories there are two more perspectives, how businesses can be delineated: First, depending on their goal, they can act for-profit or non-profit. Second, depending on their organization, businesses can operate either B2P (business-to-peer) or P2P (peer-to-peer).[14]

Arun Sundararajan, Professor and expert on economics of digital goods and network effects,[15] who refers to sharing economy as "crowd-based capitalism"[16], follows a different, more abstract approach. He describes sharing economy as "an economic system with […] five characteristics:

1. Largely market-based: the sharing economy creates markets that enable the exchange of goods and the emergence of new services, resulting in potentially higher levels of economic activity.
2. High-impact capital: the sharing economy opens new opportunities for everything, from assets and skills to time and money, to be used at levels closer to their full capacity.
3. Crowd-based "networks" rather than centralized institutions or "hierarchies": the supply of capital and labor comes from decentralized crowds of individuals rather than corporate or state aggregates; future exchange may be mediated by distributed crowd-based marketplaces rather than by centralized third parties.
4. Blurring lines between the personal and the professional: the supply of labor and services often commercializes and scales peer-to-peer activities like giving someone a ride or lending someone money, activities which used to be considered "personal".
5. Blurring lines between fully employed and casual labor, between independent and dependent employment, between work and leisure: many traditionally full-time jobs are supplanted by contract work that features a continuum of levels of time commitment, granularity, economic dependence, and entrepreneurship."[17]

[13] Schor (2016), p. 2.

[14] Cf. Ibid., p. 5.

[15] NYU Stern School of Business (2017).

[16] Sundararajan (2016), p.27.

[17] Ibid., pp. 26f.

These are only two approaches to define sharing economy, most definitely, even more exist. In order to give an overview over different business models, Schor's approach seems more suitable for this paper.
An indicator for the importance of sharing economy platforms is the amount of venture capital (VC) raised by those platforms (see figure 2). The platforms presented in this paper, Uber (see chapter 3.2), Airbnb (chapter 2.2) and obviously BlaBlaCar, can be found in this overview.

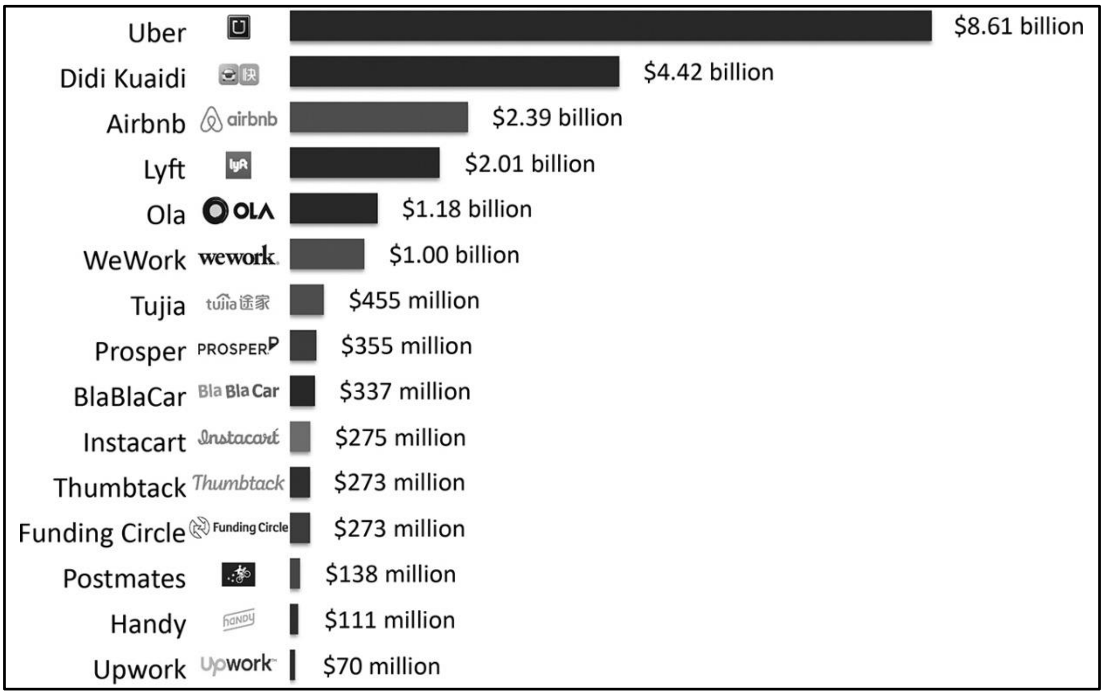

Figure 2: VC raised by selected sharing economy platforms as of December 2015 (Source: Sundararajan 2016, p. 6)

2.2 Airbnb

Airbnb is one of the most named examples concerning sharing economy. Airbnb, short for "AirBed and Breakfast"[18] was launched in 2008.[19] Founder and CEO Brian Chesky combined two simple problems: He needed money to pay his rent and due to a convention in his home town San Francisco, all hotels were sold out. Taking advantage of this increased demand in beds, he put up some airbeds and turned his apartment into a bed and breakfast.[20]

For the last years Airbnb experienced a massive growth and became a popular online marketplace for short-term rentals.[21] It "defines itself as 'a social website that connects people who have space to spare with those who are looking for a place to stay.'"[22]Airbnb-users who offer their spare rooms or apartments, called "hosts", set a price (nightly, weekly or monthly)[23] and users who need a place to stay, so called "guests" can look for these listings depending on the desired location and period of time.[24]

Airbnb's business model, contrary to other platforms, is to derive revenue from both sides, hosts and guests. While hosts are only charged with three per cent, guests pay 9-12 per cent service fee.

By 2016, 70 million guests have used Airbnb to find a place to stay, 40 million more than the first seven years combined.[25] Current numbers confirm this development. According to Airbnb, operating with more than three million listings in more than 65,000 cities in 191 countries lead to a rise of total guests to over 200 million.[26] In October 2014, Airbnb was valued at more than $13 billion, while the International Hotel Group, biggest hotel chain in the world had a market cap of $10 billion (March 2015).[27]

[18] Ibid., p. 7.

[19] Cf. Zervas et al. (2014), p. 7.

[20] Cf. Sundararajan (2016), p. 7.

[21] Cf. Edelman and Luca (2014), p.3.

[22] Zervas et al. (2014), p. 7.

[23] Cf. Ibid., p. 7.

[24] Cf. Edelman and Luca (2014), p. 4.

[25] Cf. Sundararajan (2016), p. 8.

[26] Cf. Airbnb (2017).

[27] Cf. Wallsten (2015), p. 3f.

2.3 Crowdfunding

Another phenomenon of the sharing economy is "crowdfunding", a rather new way of making investments. The business models can be divided into four categories:

1. Donation-Based Crowdfunding
2. Reward-Based Crowdfunding
3. Equity-Based Crowdfunding
4. Lending-Based Crowdfunding

Donation-Based Crowdfunding can be compared with donating money with no *real* benefit. The motivation is to do something for a good cause. Unlike traditional charities, people can choose projects to donate to in a simply way. The most popular platform in Germany is "betterplace.org", where regional, as well as international projects can be found.[28]

The leading crowdfunding platform "Kickstarter",[29] as well as other similar platforms can be associated with the most common form, the Reward-Based Crowdfunding.[30] Backers support creative projects expecting non-monetary rewards. One of the most prominent and largest crowdfunded projects on Kickstarter is the Pebble Watch. The original goal of $100,000 was reached very quickly. Over 65,000 backers donated over $10.2 million in just 37 days to support the idea of a smart watch.[31] Since its start in 2009, over $3.2 billion were donated to fund over 130,000 projects.[32]

The third form, Equity-Based Crowdfunding, helps start-ups to get capital on the one side, as well as feedback, on the other side. Investments made can generate a rate of return.[33]

The last kind of crowdfunding, Lending-Based Crowdfunding, can be regarded as a peer-to-peer granting of credits. Backers provide money for a fixed rate and period of time on platforms like "smava", "auxmoney" or "eLolly". Compared to traditional bank credits, it is less administrative burden for the borrowers and backers can choose who will get their money which leads to a social effect.[34]

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[28] Cf. Schmiedgen (2014), pp. 121ff.

[29] Cf. Kuppuswamy and Bayus (2015), p. 1.

[30] Cf. Schmiedgen (2014), p. 124.

[31] Cf. Kuppuswamy and Bayus (2015), p. 1.

[32] Cf. Kickstarter (2017).

[33] Cf. Schmiedgen (2014), pp. 125ff.

[34] Cf. Ibid., p. 130.

3 Business Models of "Sharing your Car"

Besides the concept of sharing apartments or money, sharing cars seems to play a rather big role in context of sharing economy.[35] The idea of ride sharing could already be seen during the 1970's energy crisis and World War II, when resources were short.[36] But over the last years, different kinds of business models emerged. Teubner and Flath developed a framework to categorize the multiple forms of shared mobility (see figure 3).

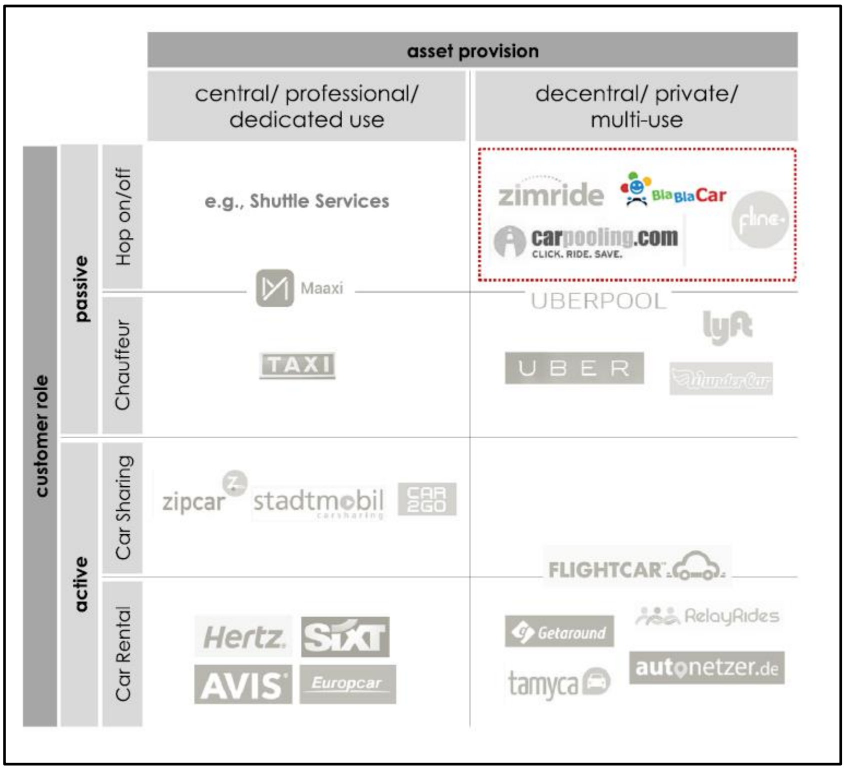

Figure 3: Taxonomy of car-based shared mobility systems
(Source: Based on Teubner et al. 2015, p. 313)

The authors use two main dimensions, "asset provision" and "customer role". The asset provision distinguishes between central and professional usage, including taxi services or traditional car rentals, and decentral and private usage. BlaBlaCar and Uber, although working with different business models are the most known actors in this dimension.

The second dimension, "customer role", is divided into active and passive users. While active users drive the car, passive users act as passengers.[37]

[35] Cf. Sundararajan (2016), p. 16.

[36] Cf. Teubner and Flath (2015), p.312.

[37] Cf. Ibid., p. 313.

3.1 BlaBlaCar

3.1.1 History

The idea for BlaBlaCar was born on Christmas 2003, when founder Frédéric Mazella wanted to visit his family in the French Countryside. He had no car and other options were not available. While travelling home with his sister eventually, he saw many people who travelled alone. In his opinion, this behavior was bad in an economical and an ecological way. Why not share empty seats (and with it costs) with people who have no car?

It took almost three years until BlaBlaCar officially launched in September 2006 in France. In the next ten years, BlaBlaCar expanded in over 20 countries (see figure 4) and now it is the world's leading carpooling platform.[38] Meanwhile BlaBlaCar has over 45 million members worldwide. Every quarter of the year, 12 million people use the carpooling platform for their journeys.[39]

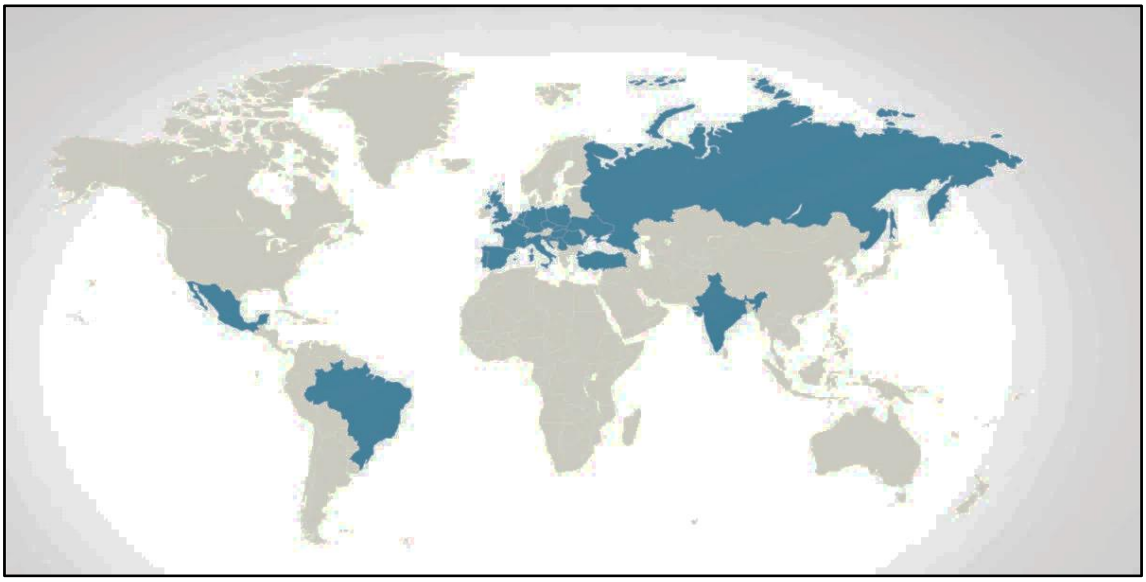

Figure 4: Map of countries where BlaBlaCar is active
(Source: BlaBlaCar 2017k)

[38] Cf. BlaBlaCar (2017a); Sundararajan (2016), p. 2.

[39] Cf. BlaBlaCar (2017k).

3.1.2 Business Model

All examples of sharing economy covered in this paper (Airbnb, BlaBlaCar, eBay, Kickstarter, Uber etc.) have one thing in common. By minimizing transaction costs, these platforms bring together two kinds of groups, in general "buyers" and "sellers"; to be more specific: Airbnb connects people with spare rooms with travelers who need a place to stay, BlaBlaCar connects drivers with empty seats in their car with passengers with the same destination and Kickstarter helps innovators with ideas meeting investors to support these ideas.[40]

These platforms are defined in two different ways, while some experts refer to "two-sided markets" or more general "multi-sided markets" with two group of economic agents[41], others refer to "peer-to-peer markets" where the platform is only an intermediary that helps matching buyers and sellers.[42]

Another asset mentioned especially associated with internet platforms like Facebook or Uber are (direct) network effects. The gain in popularity of those platforms shows that "the value of a product […] increases as the number of users grows". The default definition of direct network effects explained by the access to the telephone network can be seen in figure 5.

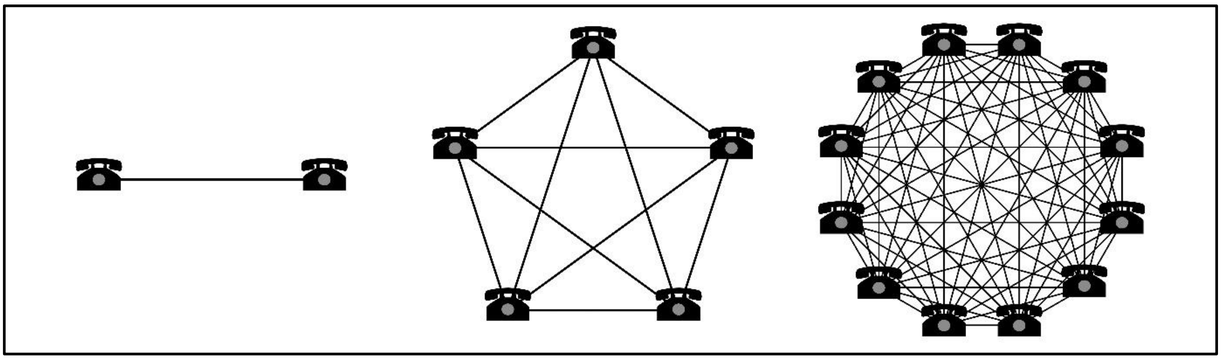

Figure 5: Network effects
(Source: Mahlkow 2016)

It is easy to understand that a network of two telephones is valued much lower than a network of twelve telephones.[43] This effect can be transferred to ridesharing platforms: the more drivers registered, the more possible offers can be expected. Consequently, a bigger network should

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[40] Cf. Einav et al. (2016), p. 615ff.

[41] Cf. Farajallah et al. (2016), p.2 citing Rochet and Tirole (2006) and Evans et al. (2011).

[42] Cf. Farajallah et al. (2016), p.2; Einav et al. (2016).

[43] Cf. Mahlkow (2016).

result in a bigger competition. Whether this competition is based on price or on other parameters which are seen more importantly by potential passengers will be discussed in chapter 4.2.

3.2 Uber vs. BlaBlaCar

Since Uber is used as a synonym for ridesharing, at least in countries like the USA, a paper about the ridesharing platform BlaBlaCar without mentioning Uber would be incomplete.

Uber, originally UberCab, and usually used when talking about UberX was founded in San Francisco in 2010 as a traditional taxi company. UberX, a ridesharing service was introduced in 2012. Contrary to traditional cabs, *every* member with a car and a driving license can become a chauffeur.[44]

The term "chauffeur" is the key difference to BlaBlaCar. Some experts refer to Uber not as a ridesharing service, but as an on-demand taxi service. While BlaBlaCar users offer seats on trips that would be unused otherwise, Uber members use their smartphone app to call a driver to their location.[45]

One can say that the main difference between Uber and BlaBlaCar is the point of view. While BlaBlaCar is supply-driven, Uber works, as mentioned above, "on-demand".

Uber is a popular platform in the USA, it faces bans in European countries like Germany or France. German courts see Uber's business model as a "violation of local transport laws if it uses drivers who are not licensed by the state in order to cut costs".[46]

[44] Cf. Feeney (2015), p. 2.

[45] Cf. Wallsten (2015), p. 4.

[46] Cf. Davies (2016).

4 Empirical Data Analysis

4.1 Preparation

The first step of an empirical analysis is to define the scope. In this case, two dimensions had to be defined. The first one is to decide which trips will be analyzed. Fortunately, BlaBlaCar represents the most popular rides in Germany on their website.[47] It was conspicuous that most of the cities in the list of popular rides are at the top of the most populous cities in Germany.[48] The cities which are used as departure and arrival places in this analysis are: Berlin, Hamburg, Munich, Cologne, Frankfurt/Main, Stuttgart, Dusseldorf, Dortmund, Essen, Leipzig, Bremen, Dresden, Hanover, Nuremberg, Duisburg, Chemnitz and Kiel. Figure 6 illustrates the featured cities and their location in Germany. It depicts the destinations which are spread across the whole country.

Figure 6: Map of Germany with featured cities indicated
(Source: Own figure; Google Inc. 2017)

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[47] Cf. BlaBlaCar (2017b); BlaBlaCar (2017h).

[48] Last updated 2015; Cf. Statista (2016).

The choice of places is based on two plausible reasons. First, locations are evenly distributed. There are cities in every region and in almost every state. This distribution leads to the second benefit: The distance between those cities varies from very short, for example trips within the Ruhr Area (Dortmund, Essen and Duisburg), over medium-length-trips of about 300 km, which represents the mean distance of all trips,[49] to trips with distances of over 800 km (Kiel to Munich and vice versa).

The second dimension is to consider which parameters can be used and which of those could affect the price and the demand of these trips. The analysis and its results in this paper can (at least in some points) be compared with a similar analysis from France.[50] The parameters can be categorized into four types. First, trip-specific parameters like the price set by the driver. Second, basic information about driver and car. Third, personal preferences like talking behavior and last parameters which can be influenced, but not set by the driver like the feedback received in past trips. The following section will explain every parameter used in the regression. It also gives some descriptive information. An overview over these descriptive statistics can be found in Appendix B.

Price

The price is used both as explained and as explanatory variable in the regression. On the one hand, seen as the explained variable, the regression exhibits which variables affects the price, on the other hand, the price can also be a parameter that may affect the number of sold seats.

Contrary to other services like Uber (see chapter 3.1), drivers set their price for themselves, BlaBlaCar only gives an advice. This recommendation depends on the length of the trip and the price is usually about €5/100 km per seat.[51] The driver sets the price with a deviation of ±50 per cent.[52]

<u>Example</u>: For the trip from Berlin to Hamburg (and vice versa), BlaBlaCar recommends a price of €14 which results in a price of €4.86/100 km. The analysis for this certain trip (N=6655) shows an average price of €13.85 (€4.80/100 km).

Since August 2016,[53] BlaBlaCar adds a commission based on the price the driver sets. This

[49] Cf. BlaBlaCar (2017k);

[50] Cf. Farajallah et al. (2016).

[51] The analysis shows, that the average price per 100 km is about €5.18.

[52] Cf. Farajallah et al. (2016), p. 7.

[53] Cf. Franz (2016).

mechanism can be seen in table 2. Passengers pay the price plus commission via PayPal or credit card. After the trip was confirmed by both driver and passenger, the money is transferred to the driver's bank or PayPal account.[54] To avoid biased results, the regressions are based on the price without commission.

Table 2: Pricing mechanism

(Source: BlaBlaCar 2017j)

Price without commission	**Commission**
€1-€5	€1
€6-€14	€2
€15-€25	€3
€26-€37	€4
€38-€49	€5
€50+	(1.1 + 0.07 × Price without commission) × 1.19 Approximated to the next €0.50

[54] Cf. BlaBlaCar (2017d).

Weekend

The second trip-related variable is the departure time, more specifically the weekday of departure. Considering the average distance of trips is about 300 km, it is more likely that many users see car-pooling rather as a substitution to intercity busses and -trains than an everyday ride. Figure 7 shows a significantly higher share of offers on Fridays (23.98 per cent) and Sundays (24.76 per cent).

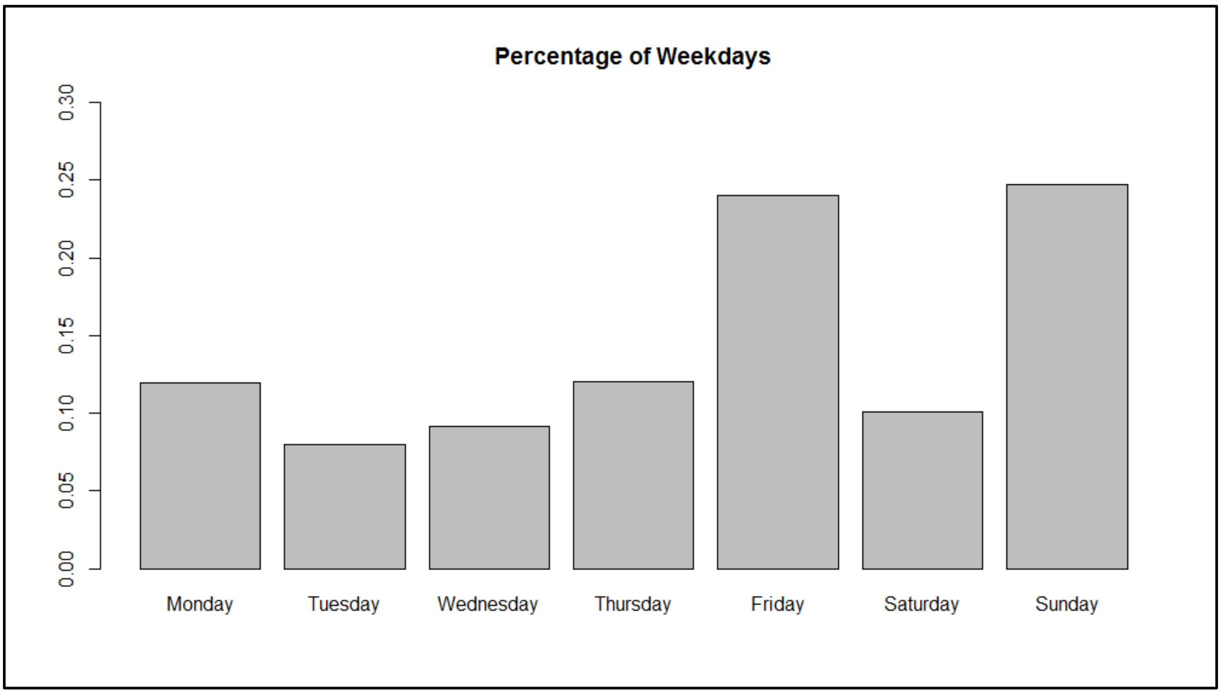

Figure 7: Percentage of weekdays complete

Another trend is observable when the trip's distance is comparatively small. Looking at trips between Cologne and Dusseldorf which are only 44 km apart, the distribution of weekdays looks very different. The most trips are offered on business days (combined 89.75 per cent), remaining only 4.81 per cent on Saturdays and 5.45 per cent on Sundays. The distribution is visualized in figure 8. Comparing these statistics, the variable "weekend" was generated. In this case, it seems reasonable to define weekends as Friday, Saturday or Sunday.

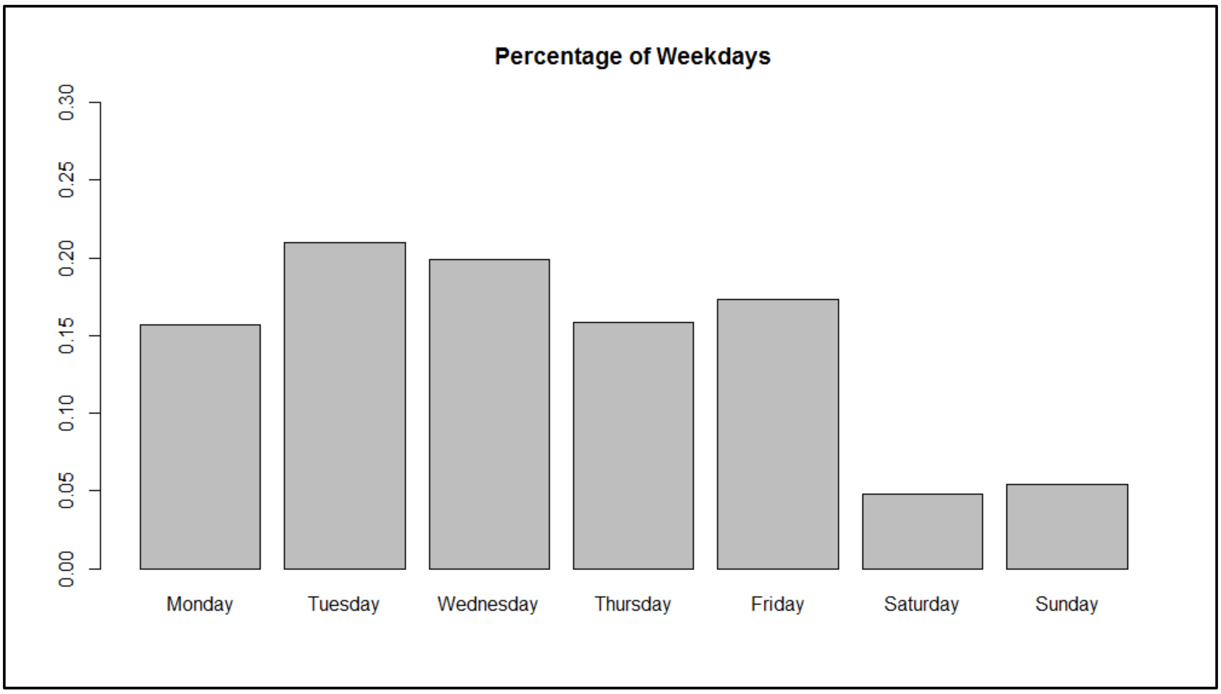

Figure 8: Percentage of weekdays (Cologne-Dusseldorf)

Profile Picture

"Trust is built on first impressions." This is not just a phrase, it is part of BlaBlaCar's trust policy. Members are recommended to add a profile picture, so possible co-drivers get to know each other even before they meet in real life. About 79 per cent of the members presented in this study have set a profile picture.

Gender

The second driver-related variable is the member's gender. Some women prefer travelling with other women, because of trust issues. The clear majority of rides (99.4 per cent) is offered to both men and women, but there is an option called "ladies only" which allows female drivers to offer rides to women only. These trips are only visible for logged in, female members.[55] Even though there are only few rides with this feature, it would be interesting to analyze these trips separated from "normal" trips. Due to BlaBlaCar's restrictions, this was not possible. Nevertheless, it is striking to see that only about 22.5 per cent of all drivers are female.

Age

Since driving is not legal under the age of 18 in Germany, it is no surprise that the youngest drivers found are 18, while the oldest are 103.[56] The average driver is 32.98 years old with a median of 30 years. Especially, the median strengthens the assumption that BlaBlaCar is often used by students (36 per cent)[57] who cannot afford an own car or do not want to buy one. Studies show that the car is no status symbol anymore. Additionally, younger people do not need an own car anymore, first large cities do not offer enough parking space and second there are many, often cheaper and environmentally friendlier, alternatives.[58]

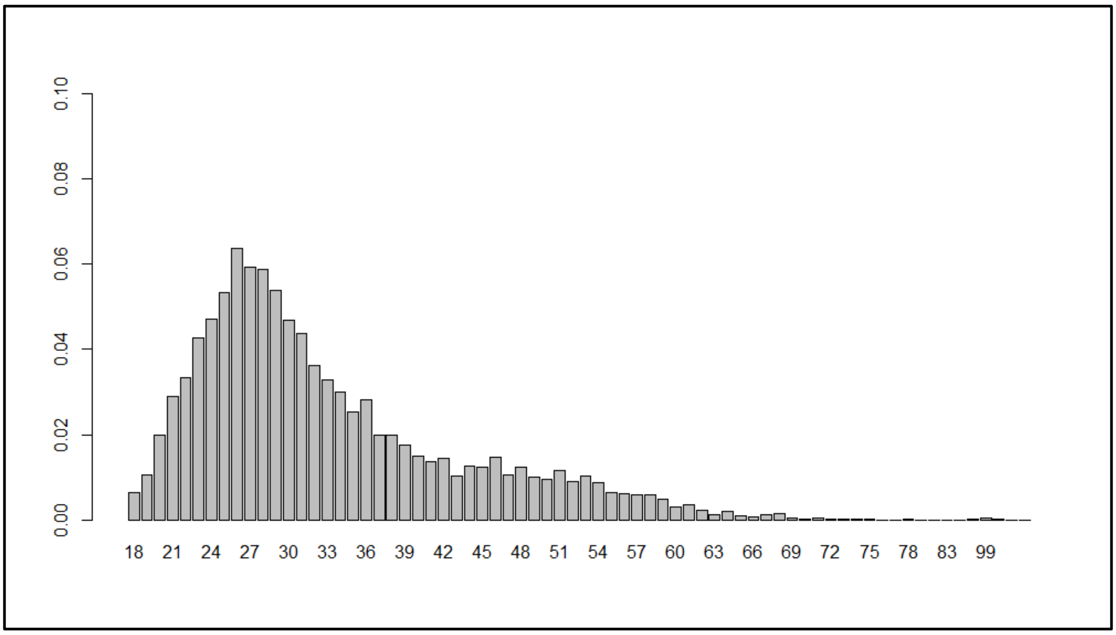

Figure 9: Age distribution

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[55] Cf. BlaBlaCar (2017f).

[56] Author's note: The maximum age is the result of this analysis. Some members seem to cheat with their age, but I think that average and median of this analysis are pretty accurate, only 141 of 250861 observations show an age of older than 70. Additionally, the findings are comparable to those of Farajallah et al. (2016), p. 6.

[57] Cf. Ibid., p. 6.

[58] Cf. Straßmann (2016).

Booking Mode

BlaBlaCar offers two kinds of booking modes. Drivers can choose between a manual and an automatic confirmation for their passengers. The option to choose makes it more difficult to interpret the results of the analysis, because only with automatic confirmation, it can be assured whether seats are sold or not. If drivers prefer manual confirmation, they do not have to declare sold seats. The analysis shows that about 39.5 per cent of drivers prefer automatic confirmation.

Car Class

When drivers set up their profile, they are asked to give information about the car like brand, model, color and vehicle type. Based on these information, BlaBlaCar classifies the cars into four categories: “Basic”, “Normal”, “Comfortable” and “Luxury”. Even though these categories are not displayed, it simplifies the comparison of different car models for analyses like this.

Only 2.18 per cent of all observations use basic cars. The biggest share with 63.35 per cent are normal cars, followed by 28.37 per cent comfortable cars and only 6.09 per cent use vehicles of the luxury class. The average car got a rating of 2.38. The findings are visualized in figure 10.

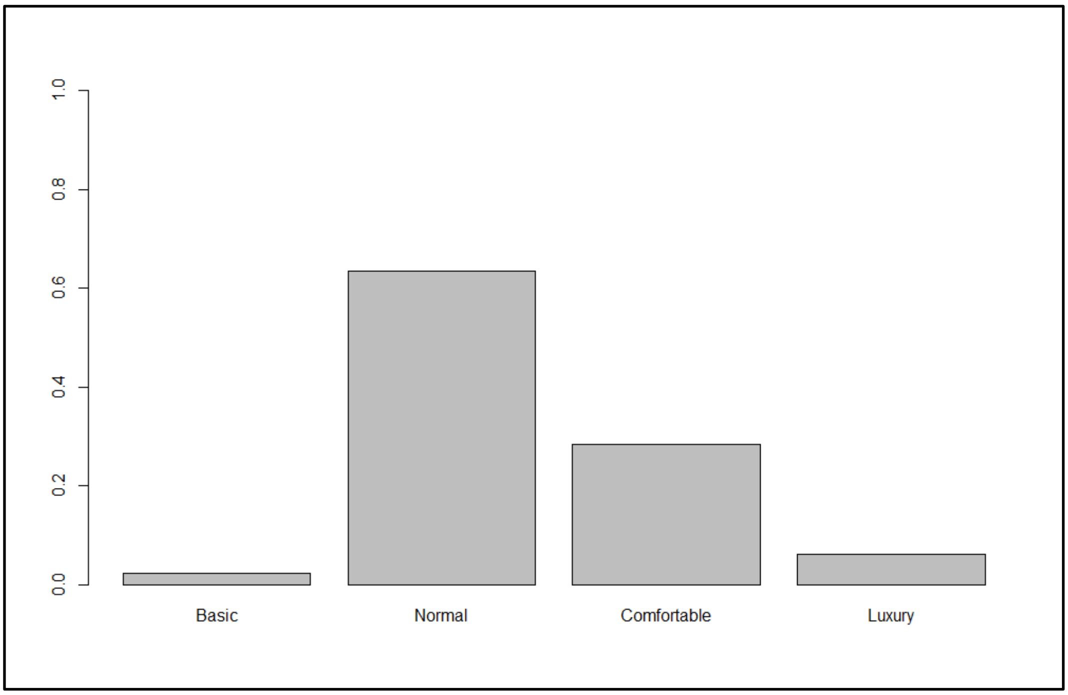

Figure 10: Distribution of comfort in cars

Comfort

Drivers guarantee that not more than two passengers will be on the backseat. Especially for long trips, this can be an important parameter for customers to decide between different offers. This comfort is guaranteed by about 74.25 per cent of all drivers.

In order to match future passengers with their own habits, drivers describe their social behavior, giving preferences in talking, smoking, music and pets:

"Blabla"

BlaBlaCar got its name from the French word "blabla" which is the equivalent for the English word "blah".[59] Members can describe their talking behavior with three categories:

- Bla: "I'm the quiet type"
- BlaBla: "I talk depending on my mood"
- BlaBlaBla: "I love to chat"

Talking behavior is treated as "talking" and "no talking", in order to simplify the regression in the next step, because "BlaBla" describes the general will to talk.

The other three variables, "Smoking", "Music" and "Pets" work analog to the first variable including the simplification:

Smoking

- "No Smoking in my car please"
- "Smoking in the car is sometimes OK"
- "Smoking in the car doesn't bother me"

Music

- "Silence is golden"
- "I listen to music if I fancy it"
- "It's all about the playlist!"

Pets

- "No pets please"
- "Depends on the animal"
- "Pets are fine. Woof!"

[59] Cf. Farajallah et al. (2016), p. 6.

Ratings

One of BlaBlaCar's key features to build up trust among members is the rating system.[60] After travelling together, drivers and passengers can grade each other using a five-star-rating-system (1 star: "very disappointing", 2 stars: "poor", 3 stars: "good", 4 stars: "excellent", 5 stars: "outstanding")[61] and may add a personal comment. These ratings can be found in two variables, "rating quality" and "rating quantity". With an average of 31.22 received ratings, drivers usually receive the best grade. The average of 3.24 "stars" can be misleading, because the analysis shows that drivers are either graded rated with 5 stars (61.74 per cent) or not at all (34.07 per cent) (see figure 11).

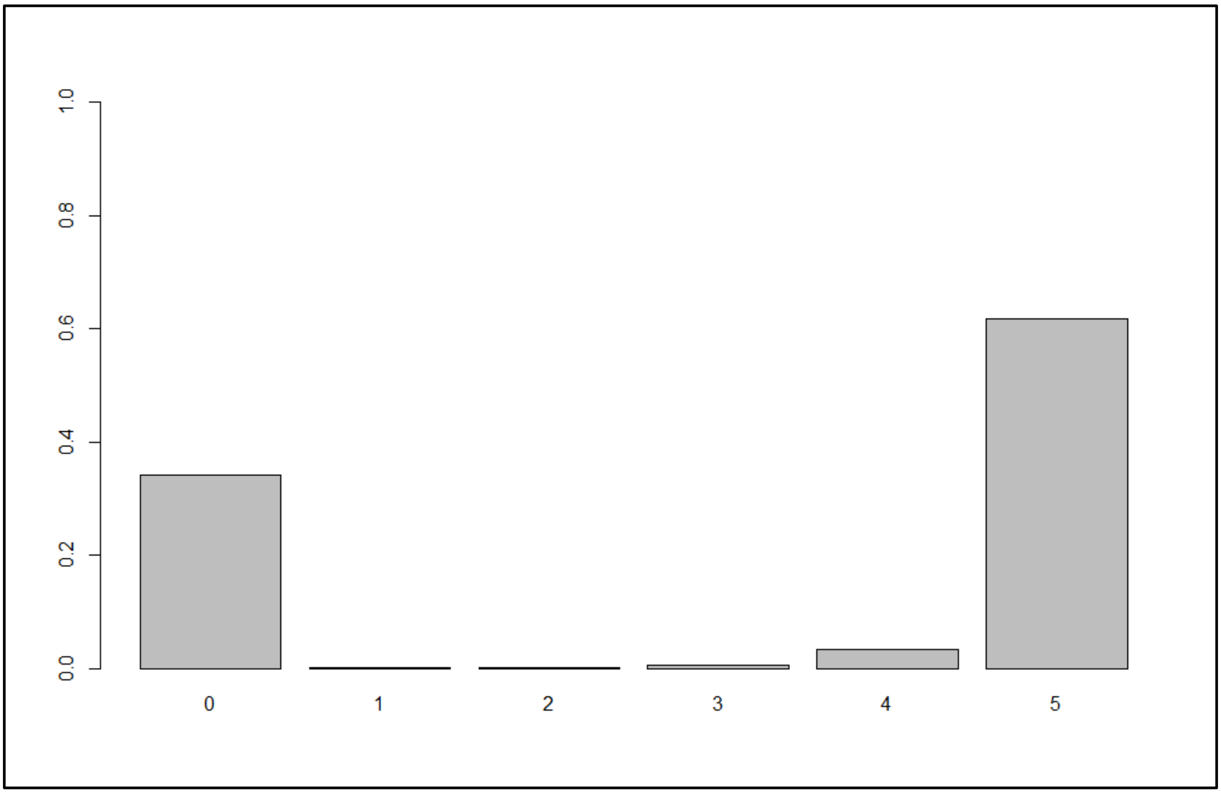

Figure 11: Distribution of ratings

[60] Cf. BlaBlaCar (2017i).

[61] Cf. BlaBlaCar (2017g).

Status

Another mechanism which correlates with rating quality and -quantity is the driver's status. Depending on different factors (see table 3), members achieve a certain status. As one result of the regression analysis, ratings as well as status should have a similar effect on the explained variable.

Table 3: BlaBlaCar's experience levels
(Source: Based on BlaBlaCar 2017e)

	Newcomer	**Intermediate**	**Experienced**	**Expert**	**Ambassador**
Verified email and phone	Welcome!	✓✓	✓✓	✓✓	✓✓
Preferences set		✓	✓	✓	✓
Profile photo added				✓	✓
# positive ratings received		★ 1 rating	★ 3 ratings	★ 6 ratings	★ 12 ratings
% of positive ratings received		★ >60%	★ >70%	★ >80%	★ >90%
Seniority		1 month	3 months	6 months	12 months

4.2 Regression Results

The following chapter shows the results of two regression analyses. The first part examines which parameters affect the price (without commission), in which way and the second explains which variables affect the number of sold seats.

4.2.1 Price

As explained in chapter 1.3.2, the regression is based on the following universal economic model:

$$y = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k + u$$[62]

with y = price (without commission) and 14 regressors (see table 4) which results in the following economic model:

$$y_{price} = \beta_0 + \beta_1 x_1 + \cdots + \beta_{14} x_{14} + u$$

Hypothesis:

As drivers gain experience and reputation, it could be possible that these more experienced drivers set higher prices than drivers with low experience and/or reputation. Multiple studies show the existence of this effect, even though it is comparably small and have a low level of statistical significance.[63] Since weekends are more popular than weekdays, it can also be a possible variable to increase the price. Additionally, the comfort should not be ignored. A more comfortable, ergo more expensive car, might lead to a higher price for the passengers.

[62] Cf. Wooldridge (2008) p. 71.

[63] Cf. Cabral and Hortacsu (2010), p. 55f.

Table 4: Regression results (All observations)[64]

	Price
(Intercept)	18.056
	(1.039)***
Instant driver approval	-0.772
	(0.127)***
Comfort=true	-0.008
	(0.140)
Car Class	1.099
	(0.118)***
Age	0.065
	(0.006)***
Status	-0.080
	(0.063)
Rating_quality	-0.080
	(0.035)*
Rating_quantity	-0.034
	(0.003)***
Blabla	-0.562
	(0.239)*
Smoking	0.303
	(0.142)*
Pet	-0.458
	(0.129)***
Music	-0.155
	(0.942)
ProfilePicture	0.048
	(0.168)
Gender=female	-0.330
	(0.139)*
Weekend	-0.031
	(0.122)
N	27033[65]
F Stat	32.16

[64] Note: For this table and, unless not stated otherwise, subsequent tables, standard errors are in parentheses;
• $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
[65] Note: 223828 observations were deleted due to missingness.

Results

To begin with confirmed assumptions, the analysis shows that in fact the car class has the biggest impact on the price. A higher car class increases the price. In contrast to the expectation, variables of reputation (status, rating quality and -quantity) have a very small, even negative effect on the price. This result shows a lower significance level than the variable of car class as well.

It is also noticeable that social parameters' effects (talking, smoking, music and pets) are higher valued than reputational aspects. While talking, pets and music have a negative impact on the price, the permission to smoke increases it. It can also be seen that older drivers charge slightly higher prices and female drivers in average charge €0.33 less than men. Although weekend-trips are more popular than trips on weekdays, they are cheaper.

Comparison with another paper

These findings confirm the analysis for BlaBlaCar-users in France (see table 5): While the effect of reputation on the price is rather small and, in case of status, even negative, the effect of more comfortable cars is noticeable: Drivers of cars with "basic" or "normal" class offer their trips much cheaper than drivers with comfortable or luxury vehicles. Contrary to the findings in this paper, French women demand higher prices than French men.

Table 5: Regression results
(Source: based on Farajallah et al. 2016, p. 38.)[66]

	Price
Manual driver approval	0.509
	(0.008)***
Car Class=1	-0.329
	(0.018)***
Car Class=2	-0.189
	(0.012)***
Car Class=3	0.017
	(0.012)
Car Class=4	0.314
	(0.016)***
Age	0.006
	(0.006***
Status=2	-0.149
	(0.009)***
Status=3	-0.276
	(0.010)***
Status=4	-0.396
	(0.010)***
Status=5	-0.445
	(0.012)***
Rating_quality	0.003
	(0.001)**
Rating_quantity	-0.000
	(0.000)
Smoking	0.143
	(0.013)***
Pet	-0.204
	(0.011)***
Music	-0.114
	(0.007)***
ProfilePicture	-0.010
	(0.007)
Gender=female	0.130
	(0.007)**
N	948789
F Stat	1706.587

[66] Note: For this table, standard errors are in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Based on observations concerning weekdays and trip distance in section 4.1, it could also be possible that trips with different distances behave differently. For this reason, the dataset of all observations is separated into three groups: short, medium and long trips. Short trips are defined as trips with a length of 0-100 km, medium trips with a distance from 100 to 400 km and long trips with at least 400 km.[67] The regression results can be seen in table 6 in comparison with observations of all trips.

[67] Note: This regression could also be based on single trips (e.g. Berlin to Hamburg etc.) but BlaBlaCar shows also possible departure and arrival places around the desired one. This is why distances were divided in this way.

Table 6: Regression results (Comparison concerning distance)

	Price (all observations)	Price (short trips)	Price (medium trips)	Price (long trips)
(Intercept)	18.056 (1.039)***	4.995 (0.487)***	14.776 (1.775)***	29.462 (2.827)***
Instant driver approval	-0.772 (0.127)***	0.057 (0.137)	-0.589 (0.218)**	-0.819 (0.312)**
Comfort=true	-0.008 (0.140)	-0.202 (0.147)	-0.499 (0.243)*	-0.3777 (0.334)
Car Class	1.099 (0.118)***	0.397 (0.120)**	0.977 (0.199)***	0.653 (0.295)*
Age	0.065 (0.006)***	-0.001 (0.008)	0.028 (0.011)*	0.020 (0.015)
Status	-0.080 (0.063)	0.006 (0.065)	-0.418 (0.119)***	-0.415 (0.166)*
Rating_quality	-0.080 (0.035)*	-0.082 (0.039)*	0.170 (0.061)**	-0.092 (0.084)
Rating_quantity	-0.034 (0.003)***	0.001 (0.001)	0.008 (0.007)	0.008 (0.010)
Blabla	-0.562 (0.239)*	-0.151 (0.312)	-1.370 (0.466)**	-0.544 (0.636)
Smoking	0.303 (0.142)*	-0.076 (0.162)	0.223 (0.252)	0.390 (0.354)
Pet	-0.458 (0.129)***	0.082 (0.150)	-0.036 (0.232)	-0.464 (0.324)
Music	-0.155 (0.942)	NA[68] NA	-0.728 (1.610)	-0.519 (2.592)
ProfilePicture	0.048 (0.168)	-0.048 (0.168)	0.322 (0.283)	0.697 (0.411)•
Gender=female	-0.330 (0.139)*	0.134 (0.145)	0.450 (0.248)•	0.229 (0.345)
Weekend	-0.031 (0.122)	0.366 (0.140)	-0.600 (0.228)**	-0.110 (0.308)
N	27033	293[69]	3365[70]	2586[71]
F Stat	32.16	1.95	5.245	2.936

[68] Not defined because of singularities.

[69] Note: 15679 observations were deleted due to missingness.

[70] Note: 93766 observations were deleted due to missingness.

[71] Note: 55554 observations were deleted due to missingness.

Some new insights are revealed in this comparison. The assumption that a higher comfort (car class and only two people on the backseat) is valued higher for longer trips was not confirmed. Comparing short and medium trips, this assumption can be seen, but comparing medium and long trips, this effect is weakened. Analyzing the effects of reputation, it is noticeable that the feedback quality has a positive effect, when the trip is between 100 km and 400 km while it has a negative one in all other cases. The comparatively biggest impact on price in the willingness to talk is also seen in medium-length trips. The effect of weekends on the price is particularly seen when comparing short and medium long trips. While the short ones are about €0.36 more expensive on weekends, medium trips are €0.60 cheaper.

4.2.2 Seats Sold

The second part of the regression analyzes the effect of the parameters named before on the number of seats sold. Therefore, the economic model was modified to:

$$y_{seats\_sold} = \beta_0 + \beta_1 x_1 + \cdots + \beta_{15} x_{15} + u$$

Hypothesis:

Considering a market of buyers and sellers, the former would always prefer cheaper offers. Analog to the first regression, it could also be possible that more experienced drivers are chosen even if the price is higher.

Table 7: Regression results (All observations)

	Seats sold
(Intercept)	0.548
	(0.082)***
Instant driver approval	0.011
	(0.010)
Comfort=true	0.049
	(0.011)***
Price	-0.000
	(0.000)
Car Class	-0.015
	(0.009)
Age	-0.001
	(0.000)*
Status	0.017
	(0.005)***
Rating_quality	0.010
	(0.002)***
Rating_quantity	0.000
	(0.000)**
Blabla	0.025
	(0.018)
Smoking	0.003
	(0.011)
Pet	0.037
	(0.010)***
Music	-0.225
	(0.074)**
ProfilePicture	0.127
	(0.013)***
Gender=Female	-0.040
	(0.010)***
Weekend	0.100
	(0.009)***
N	27033
F Stat	31.63

Results

It is striking that the price has no effect at all as table 7 reveals. Therefore, other parameters must be considered. As presumed, reputation seem to play a decisive role here; the status, the number of ratings and the feedback quality, all have a positive effect on the number of sold seats. The finding that weekend trips are more popular that trips on business days is confirmed here. Social preferences also play a role in this regression. The willingness of talking and allowing to smoke sells seats while pets and listening to music rather frightens off possible passengers. Especially the fact that music makes an offer unattractive was not expected.

The following table gives another insight in results from a French study. As expected, the price has a negative impact on the number of sold seats. The assumption that a better reputation helps to sell seats is also confirmed. Facing this study, female drivers do not decrease the number of sold seats, in fact it is increased.

Table 8: Regression results
(Source: Farajallah et al. 2016, p. 39)

	Seats sold
Price	-0.081 (0.002)***
Manual driver approval	-0.429 (0.002)***
Car Class=1	0.012 (0.003)***
Car Class=2	0.032 (0.002)***
Car Class=3	0.030 (0.002)
Car Class=4	0.039 (0.002)***
Age	0.000 (0.000)
Status=2	0.019 (0.001)***
Status=3	0.015 (0.002)***
Status=4	0.015 (0.002)***
Status=5	0.057 (0.002)***
Rating_quality	0.002 (0.000)***
Rating_quantity	0.000 (0.000)***
Smoking	-0.001 (0.002)
Pet	-0.017 (0.002)***
Music	0.020 (0.001)***
ProfilePicture	0.005 (0.001)***
Gender=female	0.130 (0.007)**
N	948789

Analog to examining the effect of the distance on the price, a regression was also performed on the number of seats sold. Table 9 shows that the price has a higher impact when the distance is relative low. It also shows a significantly higher number of sold seats on long trips when the car is more comfortable. It seems like the permission to smoke is an important feature when booking short trips, because it has a much bigger impact than on longer trips. In addition, it is obvious that female drivers are more “accepted” on short than on longer journeys.

Table 9: Regression results (Comparison concerning distance)

	Seats sold (all observations)	Seats sold (short trips)	Seats sold (medium trips)	Seats sold (long trips)
(Intercept)	0.548	0.076	0.365	0.101
	(0.082)***	(0.363)	(0.223)	(0.282)
Instant driver approval	0.011	0.140	0.027	0.078
	(0.010)	(0.087)	(0.027)	(0.030)*
Comfort=true	0.049	0.078	0.054	0.016
	(0.011)***	(0.094)	(0.030)•	(0.032)
Price	-0.000	-0.061	-0.006	-0.011
	(0.000)	(0.046)	(0.002)**	(0.002)***
Car Class	-0.015	0.021	0.007	0.087
	(0.009)	(0.077)	(0.024)	(0.028)**
Age	-0.001	0.004	-0.000	-0.002
	(0.000)*	(0.005)	(0.001)	(0.001)
Status	0.017	0.019	0.037	-0.020
	(0.005)***	(0.041)	(0.014)*	(0.016)
Rating_quality	0.010	0.010	0.000	0.012
	(0.002)***	(0.025)	(0.007)	(0.008)
Rating_quantity	0.000	-0.001	-0.002	0.001
	(0.000)**	(0.001)	(0.000)*	(0.001)•
Blabla	0.025	-0.074	-0.091	0.006
	(0.018)	(0.198)	(0.058)	(0.062)
Smoking	0.003	0.236	0.050	0.036
	(0.011)	(0.103)*	(0.031)	(0.034)*
Pet	0.037	-0.076	0.034	0.025
	(0.010)***	(0.095)	(0.028)	(0.031)
Music	-0.225	NA	-0.041	0.298
	(0.074)**	NA	(0.200)	(0.254)
ProfilePicture	0.127	0.065	0.119	0.118
	(0.013)***	(0.126)	(0.035)***	(0.040)**
Gender=female	-0.040	0.139	-0.104	-0.086
	(0.010)***	(0.092)	(0.030)***	(0.033)*
Weekend	0.100	0.337	0.250	0.127
	(0.009)***	(0.090)***	(0.028)***	(0.030)***
N	27033	293	3365	2586
F Stat	31.63	1.977	9.563	7.006

5 Conclusion

5.1 Results

BlaBlaCar is based on a classic P2P market. Drivers can list empty seat on the website with information about the vehicle and themselves. BlaBlaCar works as an intermediary, it does not provide any cars or chauffeurs. Passengers who need a ride look for appropriate offers and contact the driver. From this point on, drivers and passengers do not need BlaBlaCar anymore, trip details are communicated via smartphone and the journey begins. After the trip, BlaBlaCar provides a rating system to other members the quality of the driver.

The two regressions performed for this paper show results which were not expected, at least not all of them:

As BlaBlaCar uses a rating system which can be compared to other P2P markets like eBay etc., it would not be surprising if drivers with more experience and a better reputation would charge higher prices for their service but they are even cheaper. It is also astonishing that women, on the one hand, charge lower prices, but on the other hand sell less seats than men, or that the general permission of pets and smoking attracts potential passengers while music puts them off. The most surprising fact in this analysis is that the price has absolutely no effect on the "popularity", ergo the number of sold seats.

5.2 Outlook

Considering the rise of the sharing economy in recent years and with it the increasing popularity of carpooling platforms, there is no hint that this trend could decline. Adding other factors like rising oil prices, the lack of parking spaces in cities and the climate change, supports the thesis that more people should use carpooling instead of traveling alone. It is not only more efficient and environmentally friendlier, it might be more fun.

If the trend continues, it could be interesting to rerun this analysis in a few years. As seen in the comparison between the study from France from 2016 and this study for Germany in 2017, there are differences, maybe in one or more years there will be more differences when people ignore the price completely and only decide by sympathy.

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Appendix A – Scraper

```r
library(jsonlite)

cities<-c("Berlin","Bremen","Chemnitz","Dortmund","Dresden","Duisburg",
          "Duesseldorf","Essen","Frankfurt","Hamburg","Hannover","Kiel",
          "Koeln","Leipzig","Muenchen","Nuernberg","Stuttgart")
           #can be extended to more cities by adding them

df2=data.frame()
df3=data.frame()
df4=data.frame()

for(i in cities){
  for(j in cities){

    url <- paste0("https://public-api.BlaBlaCar.com/api/v2/trips?locale=de_DE&_format=json&cur=EUR&fn=", i, "&tn=", j, "")
    req <- httr::GET(url, httr::add_headers(Key = "xxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxxx"))
    json <- httr::content(req, as = "text")
    trips <- fromJSON(json)

    permanent_id = trips$trips$permanent_id #unique trip id
    seats = trips$trips$seats #number of seats
    seats_left = trips$trips$seats_left #number of seats available
    departure_date = trips$trips$departure_date #date and time of departure (Format: DD/MM/YYYY HH/MM)
```

```
booking_mode = trips$trips$booking_mode #(MANUAL/AUTO) AUTO if instant driver approval is selected
is_comfort = trips$trips$is_comfort #(TRUE/FALSE) TRUE if the number of passengers on the back seat is =<2
links._front = trips$trips$links$`_front` #original link
departure_place.city_name = trips$trips$departure_place$city_name #derparture city
arrival_place.city_name = trips$trips$arrival_place$city_name #arrival city
price_without_commission.value = trips$trips$price_without_commission$value #price without commission -> what driver gets
commission.value = trips$trips$commission$value #BlaBlaCar's commission
price_with_commission.value = trips$trips$price_with_commission$value #price + commission
duration.value = trips$trips$duration$value #duration in seconds
distance.value = trips$trips$distance$value #distance in km
car.comfort_nb_star = trips$trips$car$comfort_nb_star #(1-4) car’s comfort level: 1="Basic", 2="Normal", 3="Comfortable",
4="Luxury"
name = trips$trips$user$display_name #driver’s name
age = trips$trips$user$age #driver’s age
status = trips$trips$user$grade #(1-5) driver’s status: 1="Newcomer", 2="Intermediate", 3="Experienced", 4="Expert"",
5="Ambassador"
rating_quality = trips$trips$user$rating #(0-5) average of driver’s ratings
rating_quantity = trips$trips$user$rating_count #number of driver’s ratings
blabla = trips$trips$user$dialog #(NO, MAYBE, YES) willingness to talk
smoking = trips$trips$user$smoking #(NO, MAYBE, YES) willingness to allow smoking
pet = trips$trips$user$pets #(NO, MAYBE, YES) willingness to allow pets
music = trips$trips$user$music #(NO, MAYBE, YES) willingness to listen to music
ProfilePicture = trips$trips$user$has_picture #(TRUE, FALSE) TRUE if Profile picture is set
gender = trips$trips$user$gender #(M, F, MRS) driver’s gender
```

```
df = data.frame(permanent_id,
                seats,seats_left,
                departure_date,
                booking_mode,
                is_comfort,
                links._front,
                departure_place.city_name,
                arrival_place.city_name,
                price_without_commission.value,
                commission.value,
                price_with_commission.value,
                duration.value,
                distance.value,
                car.comfort_nb_star,
                name,
                age,
                status,
                rating_quality,
                rating_quantity,
                blabla,
                smoking,
                pet,
                music,
                ProfilePicture,
                gender)
```

```
    df$blabla <- gsub("_UE_",'', df$blabla) #cleaning of some variables
    df$smoking <- gsub("_UE_",'', df$smoking)
    df$pet <- gsub("_UE_",'', df$pet)
    df$music <- gsub("_UE_",'', df$music)
    df$gender <- gsub("_UE_",'', df$gender)
    df$gender <- sub("MRS",'F', df$gender) #substituting "MRS" by "F" to get only 2 possibilities


    df2<-rbind(df,df2)}

  df3<-rbind(df,df2,df3)}

df4<-rbind(df,df2,df3)

fn = format(Sys.time(), "%Y_%m_%d_%H_%M")
write.csv(df4,file=paste(fn, ".csv"))
```

Appendix B – Overview Descriptive Statistics

Table 10: Overview descriptive statistics[72]

	All Observations	Short (≤100 km)	Medium (100 km-400 km)	Long (≥400 km)
Number of Observations	250,861	15,972	97,131	58,139
Sum of Distance	54,535,049 km	1,300,183 km	23,388,170 km	29,846,696 km
Average Price	€16.52	€4.80	€12.20	€25.64
Average Price/100km	€5.19	€5.90	€5.06	€5.00
Average Distance	318.47 km	81.40 km	240.79 km	513.37 km
Average Car Class	2.38	2.38	2.37	2.42
Average Age	32.98	33.29	33.13	34.22
Average Status	2.27	2.66	2.31	2.26
Average Rating Quality	3.24	4.05	3.72	3.42
Average Rating Quantity	31.22	57.82	36.04	33.15
Percentage Instant Driver Approval	39.50%	40.80%	39.35%	41.67%
Percentage Comfort	74.25%	72.67%	72.84%	75.17%
Percentage Blabla	94.93%	94.82%	94.23%	94.18%
Percentage Smoking	36.19%	51.38%	46.19%	43.85%
Percentage Pet	56.39%	49.97%	50.43%	51.68%
Percentage Music	94.60%	76.92%	79.70%	82.93%
Percentage Profile Picture	79.05%	80.39%	78.67%	79.16%
Percentage Female	22.47%	23.52%	22.71%	21.19%
Percentage Sold Seats	23.69%	17.24%	23.13%	27.51%

[72] Note: Only complete observations are included; observations with one or more “NA” results are ignored.

Erklärung

Ich erkläre hiermit, dass ich die vorliegende Arbeit selbständig verfasst, keine anderen als die angegebenen Quellen und Hilfsmittel benutzt sowie diesen Quellen und Hilfsmitteln wörtlich oder sinngemäß entnommenen Ausführungen als solche kenntlich gemacht habe. Die Arbeit habe ich bisher oder gleichzeitig keiner anderen Prüfungsbehörde vorgelegt.

Würzburg, den 29. September 2017 ………..……………………………...

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