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Can Emma and Lukas charge more than Mohammed and Aisha on Airbnb?

Exploring ethnicity- and gender-based discrimination on Airbnb in Germany

Abstract

In recent years the peer-to-peer accommodation-sharing platform Airbnb has been growing tremendously. One key driver for growth has been the increased establishment of trust, which, however, also facilitated discrimination through the exposure of more personal data. As the growth trend is continuing, it is important to understand the extent of discrimination, so that, if needed, counteracting measures can be introduced. Previous discrimination research about Airbnb has mainly focused on the US and did not base its studies on an underlying theory. We faced these two gaps by focusing on Germany and introducing social identity theory as the underlying concept, which explains discrimination through the existence of in- and out-groups. We programmed a web crawler that collected data of more than 76,000 Airbnb listings from the 82 largest cities in Germany and ran several OLS regressions. We find that females charge 0.58% less than males and Muslims 1.17% more than Non-Muslims. We conclude that the magnitude of the discrimination is practically spoken rather low as compared to past research (differences of up to 20%) as well as considered in absolute terms (around $1). Moreover, we found that in- and out-groups do not exist, which is in line with the low magnitude of discrimination. We conclude that our study supports the applicability of social identity theory, but further research is needed in order to test the theory in greater detail.

Keywords: Sharing economy, Airbnb, discrimination, ethnicity, gender, social identity theory

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TABLE OF CONTENTS

TABLE OF FIGURES

TABLE OF TABLES

1.Introduction

In recent years, a new type of economy has grown tremendously: the sharing economy. According to a PwC study (2016), platform revenues increased by 180% in 2 years, from $10 bn in 2013 to $28 bn in 2015. And further growth is estimated: Yaraghi and Ravi (2017) forecasted global revenues of $335 bn by 2025. An especially fast-growing business has been the home-sharing platform Airbnb, now one of the pioneers in the sharing economy with coverage in over 190 countries (Lee, 2015). Airbnb is a platform for short-term housing rentals, giving everyone the opportunity to rent houses, apartments, rooms, sofas or anything a person can stay at overnight. While in 2010 47,000 persons stayed with an Airbnb host, it has been 17 million in 2015 (McAlone, 2015), a compound annual growth rate (CAGR) of over 224%. Early this year, Airbnb managed to be bigger than the world's top five hotel brands put together: while Marriott, Hilton, Wyndham, Intercontinental and Accor have 3.9 million hotel rooms altogether, Airbnb offers 4 million listings worldwide (Wood, 2017). How has this tremendous growth been possible?

A major reason is trust that has been created among users and highly facilitated by Airbnb (Edelman & Luca, 2014). For that purpose, hosts and guests share profile pictures as well as descriptions about themselves with each other. While the platform was thriving, research has recently discovered the downside of more personalized transactions. Personal information such as profile pictures or names are essential to build trust among users, but also facilitate discrimination. Many studies have shown that discrimination exists on Airbnb against hosts (Cansoy & Schor, 2017; Wang, Xi & Gilheany, 2015) and guests (Cui, Li & Zhang, 2017; Edelman, Luca & Svirsky, 2017). For instance, Edelman and Luca (2014) discovered that Non-Black hosts charge approximately 12% more than Black hosts for the equivalent rental and Edelman et al. (2017) discovered that guests with distinctively African-American names are 16% less likely to be accepted relative to identical guests with distinctively White-sounding names. While Cheng and Foley (2018) note that digital discrimination[1] is a serious issue on Airbnb due to its rapid growth, Kakar, Voelz, Wu and Franco (2017) go even a step further. They claim that it is increasingly important to understand the dynamics at play in order to be able to counteract such developments.

What is more, discriminatory behaviour against certain groups can be observed on a global scale. One of this groups are females. According to the Global Gender Gap Report 2015, on average, women earn $10,000 less per year than men (World Economic Forum, 2015). Further studies from the US and Europe confirm that gender salary gaps exist: 22% (PayScale, 2018) and 16.2% (eurostat, 2016), respectively. What is more, the World Bank Group Report 'Women, Business and the Law 2018' revealed that women face legal discrimination on a global scale. According to their study, 104 economies have laws preventing women from working in specific jobs, 59 economies do not have laws on sexual harassment and in 18 countries, men can legally prevent their wives from working (World Bank Group, 2018).

Besides women, another group, that increasingly gets discriminated, are Muslims. According to Osiewicz (2017) recent surveys conducted in the EU indicate a rise in islamophobia since 2015, the beginning of the refugee crisis. The most recent European Islamophobia Report from 2017 revealed

[1] The term digital discrimination is used to define a range of circumstances in which a person or group is treated less favourably than another person or group based on their background and/or certain personal characteristics with regards to Internet (Cheng et al., 2017).

that Europeans' average opposition to Muslim immigration is 55%, ranging from 41% in Spain to 71% in Poland. The report concludes that "islamophobia has become a real danger to the foundations of democratic order and the values of the European Union." Looking at the US, the council on American-Islamic relations (CAIR) claims that islamophobia at the end of 2017 is worse than it has been directly after 9/11, suggesting a similar Islamophobic trend as in Europe (Buncombe, 2017).
Based on these discriminatory behaviours on a global scale, as well as the importance to understand the fast-growing sharing economy, we wanted to add to the body of current research on discrimination by investigating discrimination against females and Muslims.
We did so by collecting data of Airbnb listings directly from the Airbnb website, including the host's gender and ethnicity. Our underlying theoretical framework is based on social identity theory, which explains discrimination with the existence of in- and out-groups. According to the theory the existence of such groups could be the reason for price gaps on Airbnb. In a first step, to test whether price gaps exist on Airbnb, we ran an ordinary least square (OLS) regression with the price per night as the dependent variable and the host's ethnicity and gender as independent variables, while controlling for various other variables, such as reviews, number of pictures uploaded, etc. In a second step, we tested the existence of in- and out-groups on Airbnb by running additional OLS regressions. With the regressions we tested whether Muslim guests rather stay over proportionally with Muslim hosts and whether female guests stay over proportionally with female hosts.

1.1 Background

To make our topic understandable, this chapter gives relevant background information. The first part (1.1.1) introduces Airbnb and the second part provides definitions of relevant terms (1.1.2).

1.1.1 About Airbnb

Airbnb is a company of the so-called sharing economy and was founded in 2008 in San Francisco. It offers a platform for short-term home rentals bringing together hosts and guests. The first group, hosts, can be every person who wants to provide a house, flat, room or sofa to guests for a certain period. To become a host, one needs to create an account on Airbnb, which consist of a profile picture, the first name and a short description text (see Appendix A). Optionally, hosts can connect their profile to other profiles on social networks such as Facebook or LinkedIn or verify themselves by uploading pictures of their ID. These optional measures might increase their trustworthiness for potential guests. Besides the profiles of users, webpages for the rental objects exist. These webpages consist mainly of pictures of the rental, prices and availability, amenities, house rules and cancellation flexibility (see Appendix B). The second group on Airbnb, the guests, are persons who want to rent listings offered by hosts for a specific period. To become a guest, one also needs to create an account on Airbnb with a profile picture, first name and description. Similarly, guests can also verify their account with an ID and connect their profile to social networks.
Once a guest wants to stay in a listing, there are two options depending on what the respective host has chosen. Either the listing can be instantly booked like hotels or a request must be sent to the host which can be accepted or declined. Such a request typically includes a small introduction of the guest, the motivation for visiting the city and reasons why one wants to book the respective listing. Appendix C illustrates the Airbnb website when searching for listings.

1.1.2 Definitions

For our investigation, five terms are highly important for the understanding of the topic, therefore we want to define them in this subchapter:

Discrimination: In our thesis, we follow the definition of discrimination by Bond, McGinnity and Russell (2010) who describe discrimination as "unjustifiable negative behaviour towards a group or its members, where behaviour is adjudged to include both actions towards, and judgements/decisions about group members".

Digital discrimination: "The term digital discrimination is used to define a range of circumstances in which a person or group is treated less favourably than another person or group based on their background and/or certain personal characteristics with regards to Internet" (Cheng & Foley, 2018).

Race/Ethnicity: In the literature there are many definitions of the two terms and researchers have different opinions whether race and ethnicity are the same or distinct. We follow Gracia (2017), who defines a 'race' or 'ethnic group' as a "group of people consisting of a subgroup of individual human beings who satisfy the following two conditions: (1) each member of the group is linked by descent to another member of the group who is in turn also linked by descent to at least some third member of the group and (2) each member of the group has one or more physical features that are (i) genetically transmittable, (ii) genetically associated with the group, and (iii) perceptually perspicuous." Gracia (2017) further defines that the "properties of a member of a group are considered as 'race' or 'ethnicity'". Similar to Laouénan and Rathelot (2017), who investigated discrimination against a Muslim minority, we use the term 'ethnicity' in our thesis.

Online market: An online market is a market in which the transaction is processed online (Doleac & Stein, 2013). An online marketplace is a specific type of online market, which is further defined below.

Online marketplace: "With buyers on one side and third-party merchants on the other, online marketplaces are two-sided platforms" (Choi & Mela, 2016). These marketplaces "design products such as search ranking algorithms, reputation systems and user interfaces" (Fradkin, 2015). In our thesis the terms online marketplace and online platform are interchangeable.

1.2 Geographic focus: Germany

Within our study, we have decided to look at Germany. We did so for four reasons. First, we wanted to look at a country with a critical mass of listings to analyse for a decent sample size. Therefore, we looked at the TOP 10 countries that are visited by Airbnb users worldwide. After the US, where most research has already been conducted, most countries are located in Europe (Airbnb, 2018). Among the European countries in the TOP 10 list, the largest by population is Germany with 81.4 million inhabitants (World Population Review, 2018). Hence, we concluded that we would be able to collect a sufficient sample size in terms of Airbnb listings in Germany for our analysis.

Secondly, to the best of our knowledge, until now discrimination in Germany has been mainly studied in traditional markets such as the labour (Kaas & Manger, 2012) and the housing market (Auspurg, Hinz & Schmid, 2017). We only found one study by Laouénan and Rathelot (2017) who looked at discrimination on Airbnb in several countries in Europe, in which Berlin has been considered. However, there has been no discrimination research which solely focused on a German online market. It is surprising that no studies about discrimination in online markets have been conducted in Germany yet as it is a growing field with studies investigating various platforms worldwide ranging from transportation networks (Uber by Ge, Knittel, MacKenzie & Zoepf, 2016), labour platforms (TaskRabbit and Fiverr by Hannák et al., 2017) or rental platforms (Blocket.se by Ahmed & Hammarstedt, 2008). Therefore, we want to approach this gap by investigating Germany.

Thirdly, we decided for Germany to follow the call of Kakar et al. (2017) who demanded greater geographic and demographic diversity within discrimination studies on Airbnb. Besides being a geographically unexplored area, Germany also offers an interesting mix of ethnicities. According to the German official statistical institution Statistisches Bundesamt (2017) around 18.6 million people (22% of the total population) have a migration background, including persons that either were not born with German citizenship or have at least one parent which has not been born with German citizenship. Of these, 10 million people (12% of the total population) do not own German citizenship and 1.6 million (1.9% of total population) are seeking for shelter in Germany for humanitarian reasons (Statistisches Bundesamt, 2017). Hence, we are convinced that by choosing Germany we can contribute to the current body of research by adding wider geographic and demographic insights.

Fourthly, a survey from the German Anti-Discrimination Agency from 2015 shows the extent of discrimination in Germany. Almost a third of all participants said they experienced discrimination because of their ethnicity, religion, disability, age, sexual identity or gender within the last two years. Among participants with a migration background, the numbers were even more alarming: half of them claimed to have experienced discrimination due to the named reasons (Özoğuz, 2016). What is more, the number of criminal acts towards refugee centres increased in only one year by over 500% from 199 in 2014 to 1.031 in 2015. Moreover, according to a study from Bertelsmann (2017), 57% of Non-Muslim Germans perceive Islam as a threat, 61% said that Islam does not fit into the Western world and 40% felt as strangers in their own country due to Muslims (Die Beauftragte der Bundesregierung für Migration, Flüchtlinge, und Integration, 2016). Therefore, in our eyes, Germany is an interesting location for ethnicity-based discrimination studies.

1.3 Purpose and research question

As outlined in the previous chapter, to the best of our knowledge no discrimination research has investigated the German Airbnb market yet. With that lack of research in mind, we defined the following purpose:

Purpose

We want to add to the knowledge of current discrimination research by investigating to what extent Airbnb users in Germany get discriminated.

Within discrimination, we consider ethnicity- and gender-based discrimination, which are further explained below.

Regarding ethnicity, we briefly stated in the introduction that we want to look at Muslims, by which we refer to individuals with an Arabic, Muslim name (labelled Muslim hereafter). We decided to do so mainly for two reasons.

First, Muslims are the largest minority in Germany. However, their actual number is difficult to determine as Muslims in Germany are not official members of the religion. While the German Federal Office for Migration and Refugees estimated the number of Muslims living in Germany between 4.4m and 4.7m in 2015, the American Pew Research Center estimated nearly 5m at the end of 2016, which

is nearly 6.1% of the German population (Röther, 2018). Hence, we expected a decent sample size of Muslims on Airbnb in Germany.
Second, discrimination against Muslims on Airbnb has already been found by Laouénan and Rathelot (2017), who conducted a study across 19 cities in North America and Europe. As their study only included Berlin, it is interesting to investigate whether their results can be confirmed for a greater sample of German cities.
Therefore, in our study we divide hosts regarding their ethnicity into two groups: Muslims and Non-Muslims.

Regarding gender, in our study we distinguish between female and male. We decided to look at differences between gender mainly due to the global discrimination against females. As outlined in the introduction, women earn less than men (World Economic Forum, 2015) and face legal discrimination in more than 100 countries in the world (World Bank Group, 2018). As the Airbnb guests who visit Germany come from all over the world, it is interesting to investigate whether these global discriminatory facts against females are also reflected on Airbnb.

What is more, due to technical feasibility for the data collection process, we decided to look at discrimination against hosts on Airbnb. Hence, we derived the following research question (RQ):

RQ

To what extent do Airbnb hosts in Germany get discriminated based on their ethnicity (Muslim, Non-Muslim) or gender (female, male)?

1.4 Research outline

In the subsequent chapters, we first give a literature review (Chapter 2) which ends with the identified research gap. Afterwards, we introduce the underlying theoretical framework (Chapter 3), which is followed by the hypotheses development (Chapter 4). Subsequently, the methodology of our thesis is explained (Chapter 5) including the data collection (Chapter 6) and data analysis process (Chapter 7). Chapter 8 presents the empirical results of the study and accepts or rejects the hypotheses. The thesis rounds up with a discussion (Chapter 9) as well as contributions, limitations and future research (Chapter 10).

2. Literature review

Reviewing the literature, we had two approaches to narrow the topic down (illustrated in Figure 1). First, we looked at discrimination in various markets. As we found a lot of research in both traditional and online markets, we further concentrated on the latter. Due to the fact that there were still many studies about discrimination in online markets, we narrowed the topic even further: First to online marketplaces and finally to discrimination on Airbnb.
Second, besides the market dimension, we had a geographic dimension distinguishing between Non-Germany and Germany as the latter is the focus of our study. When looking at Germany, it turned out that no one has researched discrimination on Airbnb yet. Even when looking at online marketplaces and online markets, to the best of our knowledge there are also no studies focusing on Germany. Hence, we widened the scope once more, looking at discrimination in traditional markets in Germany.

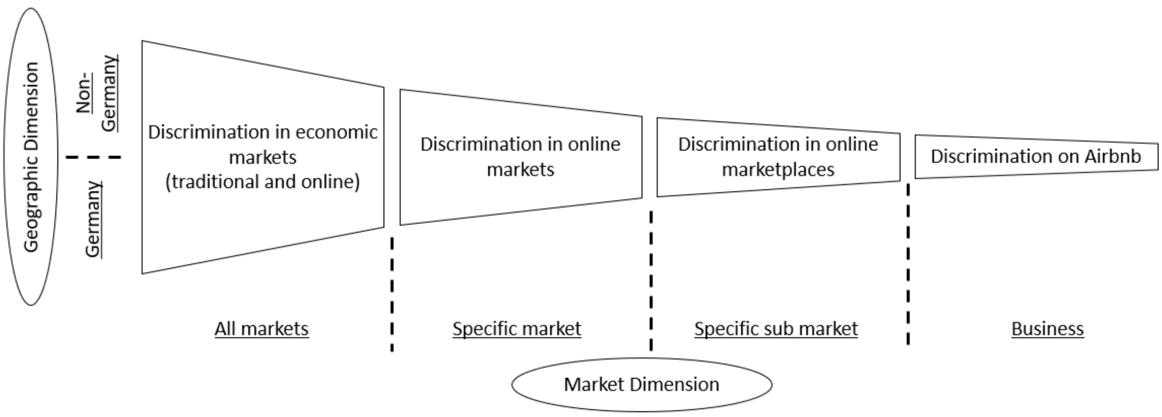

Figure 1: Screening process of the literature split in two dimensions: geographic and market dimension.

Hence, Chapter 2.1 gives an overview of discrimination on Airbnb (with no studies from Germany) and Chapter 2.2 discusses findings about discrimination in Germany. Table 1 illustrates the structure of the literature review. Finally, Chapter 2.3 summarizes the research gap.

		Market dimension		
		Airbnb		**Economic markets**
		Guests	**Hosts**	
Geographic dimension	**Non-Germany**	Edelman et al. (2017) Cui et al. (2017)	Edelman & Luca (2014) Cansoy & Schor (2017) Kakar et al. (2017) Wang et al. (2015) Laouénan & Rathelot (2017) Mohammed (2017)	
	Germany			Kaas & Manger. (2012) Auspurg et al. (2017) Machin & Puhani (2003)

Table 1: Overview of the literature review.

2.1 Discrimination on Airbnb (Non-Germany)

Regarding discrimination on Airbnb in Non-Germany markets, we distinguish between discrimination against Airbnb guests (2.1.1) and Airbnb hosts (2.1.2). In our literature review we focus on discrimination based on ethnicity and gender as the two characteristics are also the focus of our study. However, we also want to mention that more studies exist that considered discrimination against other groups, ranging from rival football team fans (Bliss & Warachka, 2017) to same sex marriages (Ahuja & Lyons, 2017).

2.1.1 Discrimination against guests

The purpose of research in this field is to investigate whether the ethnicity or gender of a guest influences the probability of being accepted by hosts. In 2017, Edelman et al. created guest accounts that were identical and only differed by name, with which they requested over 6,000 Airbnb listings. Their results show that guests with distinctively African-American names are 16% less likely to be accepted relative to identical guests with distinctively White names. Cui et al. (2017) used a similar approach with fictitious accounts. They showed that requests from guests with African-American sounding names are 19.2 percentage points less likely to be accepted than those with White-sounding names. However, they still go a bit further: as their fictitious accounts did not have any review, they experimented what happens as soon as their accounts get one positive review: the acceptance rate of African Americans rose by 29.5% to 58.2%, bringing African American's acceptance rate even on a slightly better level compared to the acceptance rate of White guests with one review (56.2%). An overview of the papers is given in Table 2.

2.1.2 Discrimination against hosts

The purpose of research in this field is to investigate whether ethnicity or gender influence the prices hosts can set. Looking at discrimination against Airbnb hosts, in 2014 Edelman and Luca collected data from the Airbnb website distinguishing between Blacks and Non-Blacks. According to their study, in New York City Non-Black hosts charge 12% more than Black hosts for equivalent rentals (controlling for information visible on the website). As their study was only limited to NYC and only distinguished between Blacks and Non-Blacks, three years later, Cansoy and Schor (2017) widened the scope. They looked at differences among Whites, Blacks and, Hispanics across all metropolitan areas in the US with a population greater than half a million. Cansoy and Schor (2017) found that a listing located in an all Non-White neighbourhood is expected to charge $13 less and have a rating that is about 2 points lower than a listing located in an All-White neighbourhood.

As African-Americans are not the only minority in the US, other studies investigated how other minorities are disadvantaged. Kakar et al. (2017) showed that in San Francisco Hispanic and Asian hosts on average have a 9.6% and 9.3% lower listing price compared to their White counterparts after controlling for neighbourhood, property values, user reviews and rental unit characteristics. However, they had a quite small sample size of only 715 listings in contrast to 3,752 listings by Edelman and Luca (2014) of NYC. In 2015, Wang et al. also investigated the Asian minority. They limited their focus to a small geographic area, only looking at Oakland and Berkeley. According to their study, Asians earn $90 less per week or 20% less than White hosts for similar rentals. However, Wang et al. (2015) did not consider socioeconomic differences on a neighbourhood level, which can have significant impacts on prices.

While most studies focus on the US, one study goes beyond the Unites States: Laouénan and Rathelot (2017) included 19 major cities in the US, Canada and Europe in their study. What is more, they looked at various minorities: African-American in the US and Arabic/Muslim in both the US and in Europe. Their results show that ethnic minority groups charge 16% less than hosts from majority groups in the same city. However, controlling for a rich set of characteristics including neighbourhood and property characteristics the price gap was reduced to 3.2%. What is more, they found out that for each review a minority host receives, the price gap reduces. In fact, for hosts with more than 50 reviews the price gap reduced down to 0.7%. What is more, Laouénan and Rathelot (2017) showed that besides the price gap, in- and out-groups do not exist on Airbnb, meaning that minority guests are not mainly staying at minority hosts. However, their results might not be representative for all considered countries as they investigated only one city per country.
Based on the mentioned studies, Airbnb was heavily criticised for its discrimination issues by several media sites (Massie, 2016; Sisson, 2016). As a reaction, the company introduced two changes in late 2016: first, all Airbnb members had to agree to Airbnb's community commitment against racism and discrimination. Secondly, pictures of hosts were relocated on the website. Since November 2016, pictures of hosts are not visible on the first page anymore, but only when potential guests click on a listing. In 2017 Mohammed looked whether these changes had any impact on discrimination on Airbnb (Mohammed, 2017). For that purpose, he collected data from Airbnb in four US cities including Los Angeles, New Orleans, Philadelphia and New York City. He concluded that the price gap was reduced by 0.01 units (logarithm of price) and that the expected bookings gap was narrowed by 0.1 units (logarithm of expected bookings) in NYC. However, estimates for Non-NYC samples were less clear-cut, making the impact of the design change almost negligible as there were minor impacts in three out of four cities.
Moving away from ethnicities and focusing on gender differences, both Edelman et al. (2017) and Kakar et al. (2017) could not find statistical significant discrimination, meaning that the gender of the host most likely does not influence the price of the listing. The results of the papers are summarized in Table 2.

2.2 Discrimination in Germany

As described earlier, this subchapter has a wider scope as discrimination in online markets in Germany is a quite unexplored area. To the best of our knowledge, we only found Laouénan and Rathelot (2017) who considered the German capital Berlin regarding their investigation of discrimination on Airbnb. However, the results cannot be extracted for Berlin as the researchers included 19 major cities in the US, Canada and Europe in their study. Widening the scope to discrimination on online marketplaces and online markets, we did not find any further studies and widened the scope even more to discrimination in traditional markets in Germany. Within that field, we found the following three studies.
In 2012 Kaas and Manger looked at the German labour market and sent two identical applications with one differentiation, one with a German-sounding name and one with a Turkish-sounding name, to 528 different firms, which had advertised for internships. According to their results, a German name raises the probability of a callback by 14%. They showed that discrimination is stronger at smaller firms, at which the German applicant receives 24% more callbacks. However, their results only account for student internships and only for students with interesting CV's and good grades. Differences between German- and Turkish-sounding names have not only been studied in the labour market, but

also in the German housing market. Auspurg et al. (2017) sent two email inquiries to over 600 rental objects in Munich which were advertised in ads. Discrimination was derived from landlord's response rates. The researchers revealed a discrimination rate against Turks of 9 percentage points. However, one must have in mind that their results are limited to Munich and only consider the first part of the process of renting an accommodation. Further discrimination might occur at later stages. Looking at differences in gender, Machin and Puhani (2003) revealed a pay gap of 28% in Germany against women. When interpreting the results, one must consider that the data they used is more than 20 years old since their data set is from 1996. Table 2 gives an overview of the mentioned studies.

Author	Methodology	Theory	Location	Guests / Hosts	Discrimination based on ethnicity	Discrimination based on gender	Limitations
Edelman et al. (2017)	Create accounts, send requests	none	USA (Baltimore, Dallas, Los Angeles, St. Louis, and Washington DC)	Guests	African-American names are 16% less likely to be accepted relative to same guests with White names.	No statistically significant findings regarding impact	Do not observe the effects of past reviews on discrimination.
Cui et al. (2017)	Create accounts, send requests.	none	USA (Boston, Chicago, Seattle)	Guests	African-American names are 19.2 percentage points less likely to be accepted than White names. A positive review eliminates gap.		
Edelman & Luca (2014)	Quantitative/ Case study / Linear regression	none	USA (NYC)	Hosts	Non-Black hosts charge approximately 12% more than Black hosts for the same rental.		Only in NYC, only distinction between Black and Non-Black.
Cansoy & Schor (2017)	Quantitative/ Case study / Linear regression	none	USA (104 metropolitan areas with population over 500,000)	Hosts	On average: in White census tract: 4 listings, $120 each, 96/100 rating / Non-White tract: 2 listings, $107 each, 94/100 rating.		
Kakar et al. (2017)	Quantitative/ Case study / Linear regression	none	USA (San Francisco)	Hosts	On average, Hispanic and Asian hosts charge 8-10% lower prices relative to their White hosts.	No statistically significant findings regarding impact	Small sample size (715 listings).
Wang et. al (2015)	Quantitative/ Case study / Linear regression	Hedonic pricing theory	USA (Oakland and Berkeley)	Hosts	On average Asian hosts earn $90 less per week or 20% less than White hosts for similar rentals.		Did not consider socio-economic differences on neighbourhood level.
Laouénan & Rathelot (2017)	Quantitative/ Case study / Linear regression	none	Europe and USA (19 cities)	Hosts	Minority hosts charge3.2% less than other hosts in same cities. An additional review reduces the gap to 0.7%.		Results might not be representative for countries as only 1 city/ country was studies.
Mohammed (2017)	Quantitative/ Case study / Linear regression	none	USA (NYC, LA, New Orleans, Philadelphia)	Hosts	Price gap decreases by 0.01 units (logarithm of price) in all four cities after design change of Airbnb website.		Results for booking gap are only clear-cut for NYC, not for the other cities.
Kaas & Manger (2012)	Quantitative / Case study / Regression	none	Germany	n.a.	German name raises probability of a callback by 14%, stronger discrimination at smaller firms.		Only student intern-ships, student had interesting/good CVs.
Auspurg et al. (2017)	Quantitative / Case study / Regression	none	Germany	n.a.	Discrimination rate against Turkish applicants of 9 percentage points.		Limited to Munich, focus only on first step in rental.
Machin & Puhani (2003)	Quantitative / Case study / Standard Blinder - Oaxaca	none	Germany	n.a.		Males earn 28% more than females. 8%-20%	Data are old, from the German Labor Force Survey 1996.

Table 2: Overview of the literature (an empty field means that this aspect was not part of the study).

From Table 2 we conclude four points: first, no paper has investigated discrimination on Airbnb in Germany yet. Second, the papers that investigated discrimination on Airbnb are focused on the United States and mainly investigated discrimination against hosts. Third, out of those studies, all used a quantitative approach and found discrimination against minorities, whereas discrimination against gender could not been proven on Airbnb yet. Fourth, no study of our literature review made use of a theory except Wang et al. (2015). However, their theory (hedonic pricing theory) explains the use of the linear regression and not discrimination itself.

2.3 Research gap

When screening the literature of discrimination on sharing economy platforms, we identified two gaps. First, the vast majority of studies of discrimination on Airbnb has been conducted in the US. As shown in Table 2, among all papers we found, only one study widened the scope by also considering Canada and Europe (Laouénan & Rathelot, 2017). Kakar et al. (2017) recently identified the research concentration on the US and called for further research in other geographic or demographic markets. Second, when going through previous literature of discrimination on Airbnb, a theoretical foundation was missing in most studies. In all papers we found, only Wang et al. (2015) based their study on hedonic pricing theory (see Table 2). However, hedonic pricing theory aims to justify why a linear regression can be used for measuring discrimination, but does not deliver an explanation for the underlying reasons of discrimination. Therefore, no previous study made use of a fundamental theory that explains discrimination.

With our thesis we want to approach the two gaps that we have identified in past research. First, we consider another geographic and demographic region by looking at Germany. Second, we base our research on social identity theory, which is introduced in the subsequent chapter.

3. Theoretical framework

Regarding a theoretical background, there are several theories explaining reasons for discrimination. In this study we focus on social identity theory, which is explained in Chapter 3.1. In a second step, Chapter 3.2 puts the theory in the context of Airbnb.

3.1 Social identity theory

Social identity theory was introduced by Tajfel and Turner in 1979 and aims to explain various forms of intergroup behaviour. In their research, Tajfel and Turner (1979) distinguish two types of groups: in-groups and out-groups. From the perspective of an individual, his or her own group is the in-group and all other groups are considered as out-groups.

Within their research of group behaviour, Tajfel and Turner (1979) screened previous literature and concluded that in-group bias is an omnipresent feature of intergroup conflicts. A number of studies have shown that the mere perception of belonging to a group is sufficient to trigger discrimination among groups. For instance, in a study by Tajfel, Billig, Bundy and Flament (1971) participants have been randomly assigned to two groups, X and Y, and given the task to allocate money to other subjects of which they only knew the group membership and the number (e.g. number 13 from group X or number 3 from group Y). The participants who allocated the money only knew their own group membership, there was neither previously existing hostility nor economic self-interest as the funds were always allocated to others. The interesting finding was that the basic intergroup categorization lead to in-group favouritism and discrimination against the out-group as subjects allocated significantly higher funds to their in-group members. From that experiment, Gerard and Hoyt (1974) concluded that (1) minimal intergroup discrimination can exist without incompatible group interests and that (2) the baseline conditions for intergroup competition are so minimal that there are “some factors inherent in the intergroup situation itself”.

Looking further into these factors, Tajfel and Turner (1979) defined what a group is and which criteria determine group memberships. For the two researchers “a group is conceptualized as a collection of individuals who (1) perceive themselves to be members of the same social category, (2) share some emotional involvement in this common definition of themselves, and (3) achieve some degree of social consensus about the evaluation of their group and of their membership of it.” The process of becoming a group member, according to them, is twofold: an individual (1) must define him/herself as a member and (2) be defined by others as a member of that group. Following that, group behaviour was defined as “any behaviour displayed by one or more actors toward one or more others that is based on the actors’ identification of themselves and the others as belonging to different social categories” (Tajfel & Turner, 1979). In that definition of group behaviour, the various behaviours are based on the groups’ identification of individuals as belonging to social categories. In that view, belonging to social categories constitutes an individual’s ‘social identity’ - the heart of social identity theory, which is further described below.

What is more, Tajfel and Turner (1979) make the basic assumption that individuals strive to maintain or enhance their self-esteem. Social identity theory is divided into three processes (Figure 2).

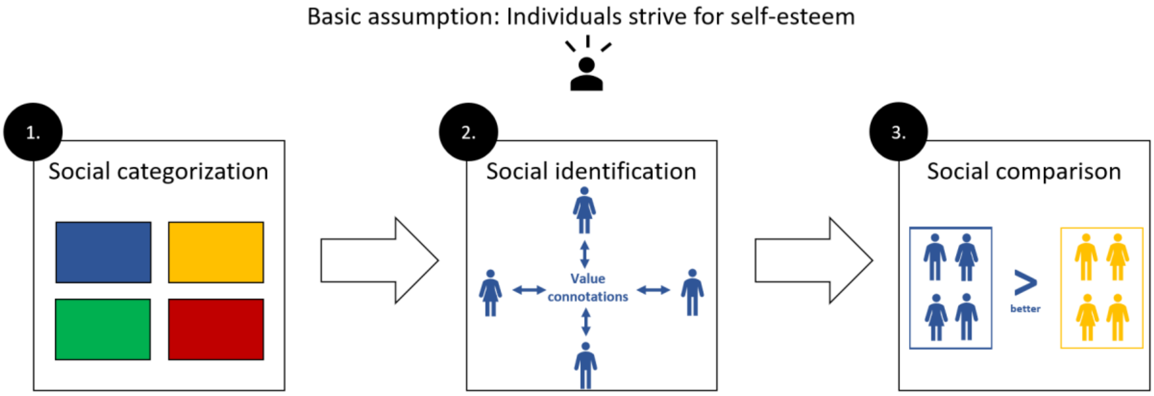

Figure 2: The three processes of social identity theory.

The first step is social categorization. Tajfel and Turner (1979) assume that social groups are categories and the membership of them is associated with positive or negative value connotations. Social categorization is an individual's cognitive tool for segmenting and classifying the social environment. In this way, social categorizations do not only order the social environment, but also provide a system of orientation for self-reference and define the individual's place in society. Social categorization also influences the way people process information about others. Taylor, Fiske, Etcoff and Ruderman (1978) found that as a result of categorization, within-group differences become minimized and between-group differences exaggerated. The process is illustrated in Figure 2. For instance, subjects might categorize themselves based on the colours they are wearing: blue, red, green and yellow. Although people might have many similarities such as ethnic background, level of wealth etc., they may perceive others as very distinct only because they are wearing differently coloured clothes.

Secondly, individuals want to join groups as they thrive for self-esteem. Therefore, they strive to achieve or maintain positive social identity. Tajfel and Turner (1979) use the term 'social identity' to describe the aspects of an individual's self-image that derives from connotations (social categories) to which an individual perceives belonging. For intergroup differentiation, the belonging is very important; individuals must have internalized their group membership as an aspect of their self-concept and be subjectively identified with their in-group. As individuals strive for a positive social identity, they join groups as social identity is provided by social groups due to an identification of members in social terms. However, a group's identification can be both positive or negative depending on the value connotations that are derived from the social categorizations. Thus, it can happen that social identity is unsatisfactory. In that case, the theory claims that individuals will either strive to leave their existing group or make their existing group more positively distinct. For instance, as illustrated in Figure 2, subjects wearing the colour blue might have the value connotation of luxurious and precious in case blue is seen as an expensive colour. People might be proud to share their wealth and they dress blue to identify with their group.

Third, the evaluation of one group is determined through social comparison with other groups in terms of value-laden attributes and characteristics (Tajfel & Turner, 1979). Based on the previous identification (process 2), individuals of one group are defined as similar or different, as 'better' or 'worse' than members of other groups. The aim of comparison with other groups is to reach superiority over these groups. Therefore, in-groups do not compare themselves with every available out-group. The out-group must be perceived as relevant for the purpose of being inferior to the

respective in-group. Similarity, proximity and situational salience are among the variables that determine out-group comparability. Situational salience refers to the fact that the social situation as such must be as to follow for inter-group comparisons that enable the selection of relevant relational attributes. For instance, in the US skin colour is a more salient attribute than in Hong Kong. These pressures for superiority lead social groups to attempt to differentiate themselves from each other even more. For example, in the social setting of our subjects, the colour of the dress might be an important fact, since it is situational salience. Moreover, subjects dressed blue might compare themselves with subjects dressed yellow as both live in the same geographic area (proximity) and the blue-dressed ones know that the yellow-dressed ones are less wealthy and, therefore, inferior.
To sum it up, the basics for discrimination according to social identity theory can be divided into three parts. First, people put other persons into categories. Second, people identify themselves with one group, called their in-group. Third, the in-group compares itself with out-groups with the aim of being superior, emphasizing the differences among the groups.
Looking at the consequences of these processes, the study by Tajfel et al. (1971) revealed how mere categorization as a group member can lead into group bias. Then, in-group members are favoured over outgroup members in evaluations and allocation of resources. In fact, across hundreds of studies it has been shown that participants rate in-group members more positively, allocate resources preferably to in-group members and want to maintain maximal difference in allocation between in-group and out-group members (Bond, 2010).

3.2 Social identity theory in the context of Airbnb

In the following we explain how the three processes of social identity theory apply to Airbnb. Figure 3 illustrates the three steps as well as the consequences as a fourth step. For illustration purposes, we explain the processes with categorization based on ethnicity and Western Europeans as the in-group and Muslims as the out-group.
First, once guests search for a listing on Airbnb, they could categorize hosts into social groups with different value connotations. When guests are screening listings, there is only few information about hosts available for a possible categorization: guests can see the host's profile picture, the host's name and a short introduction text (see Appendix A). The categorization of hosts by guests is visualised in the right column in Figure 3. Similarly, hosts could categorize guests after these have sent a request for a stay. The categorization of guests by hosts is visualized in the left column in Figure 3. With regard to our example, guests and hosts could categorize each other according to their ethnicity (top arrow in Figure 3). We assume that ethnicity can be determined in the majority of cases as often only the name or only the picture is sufficient for making accurate derivations.
In a second step, after the categorization, we further want to look at Western European guests and hosts. These guests and hosts could identify themselves and subjectively internalize with their in-group. For that purpose, they (1) perceive to be members of the same social category as other Western Europeans, (2) share some emotional involvement in this common definition of Western Europeans, and (3) achieve some degree of social consensus about the evaluation as a Western European group and their membership of it. This process is visualised as 'social identification in Figure 3.
Third, once internalized with the social group of Western Europeans, Western European guests and hosts could compare themselves with other social groups on Airbnb in order to feel superior. The social situation on Airbnb allows to do so as the ethnicity of every guest and host can be determined

by the name and profile picture. In our example, one relevant out-group are Muslims. In Figure 3, this process is shown with a double arrow labelled as 'social comparison'.

In a fourth step, we want to look at the consequences of the three previous steps. Continuing with our example, as both guests and hosts act with in-group favouritism, guest might send more requests for stays to Western European hosts and Western European hosts might accept more requests that are send from in-group members. As a consequence, Western European guests could stay more with Western European hosts (in-group) than with other hosts such as Muslim ones (out-group). Figure 3 visualizes the preferential treatment with another double arrow.

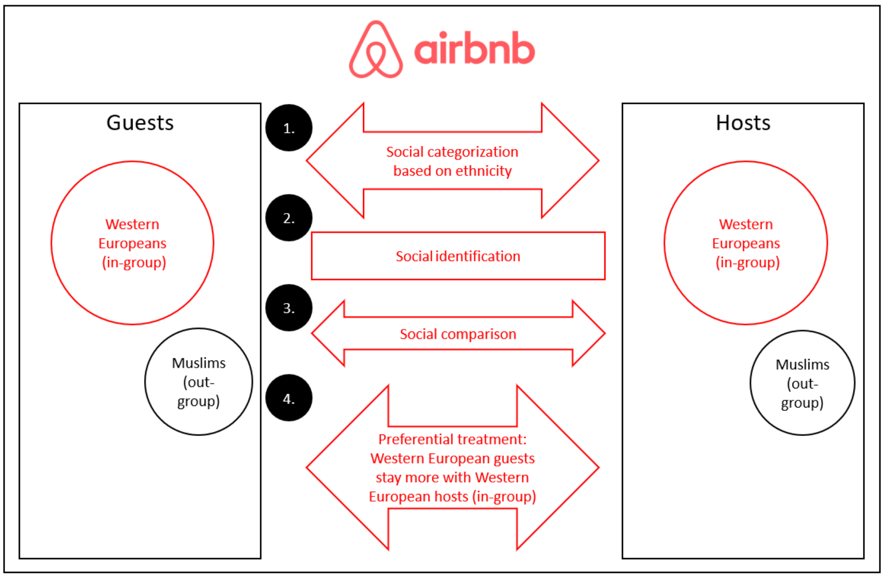

Figure 3: Social identity theory in the context of Airbnb.

4. Hypothesis Development

As briefly outlined in the introduction, we want to conduct two analyses. First, to investigate whether a price gap against hosts exists and secondly, whether in- and out groups are formed based on the criteria ethnicity and gender.
Chapter 4.1 gives the required background information for ethnicity-based discrimination and Chapter 4.2 provides that information for gender-based discrimination. Subsequently, Chapter 4.3 develops the hypothesis for testing price gaps and Chapter 4.4 the hypothesis for testing the existence of in- and out-groups based on social identity theory.

4.1 Background: Ethnicity-based discrimination

For developing the ethnicity-based hypothesis, we screened previous research for ethnicity-based discrimination in general and considered recent social global developments that might influence discriminatory behaviour against Muslims.
First, six studies revealed discrimination against Blacks: two studies against guests (Edelman et al., 2017; Cui et al., 2017) and four against hosts (Edelman & Luca., 2014; Cansoy & Schor, 2017; Mohammed, 2017, Lauénan & Rathelot, 2017). Not only Blacks are discriminated on Airbnb, but other minorities are disadvantaged as well: for instance, Wang et al. (2015) found discrimination against Asians and Kakar et al. (2017) revealed discrimination against Asians and Hispanics. While all mentioned studies focused on the US, Laouénan and Rathelot (2017) revealed that not only in the US, but also in Canada and Europe minority hosts charge less. Interestingly, Laouénan and Rathelot (2017) did not only consider Blacks, but also found a small price gap of 3.2% against the Arab/Muslim minority. Moreover, Laouénan and Rathelot (2017) looked at the existence of in- and out-groups based on the criteria Muslim[2]. Table 3 gives an overview of ethnicity-based discrimination on Airbnb.
Secondly, as stated previously, islamophobia has increased in the Western world in recent years. According to the most recent European Islamophobia Report from 2017, Europe's average opposition to Muslim immigration is 55%, concluding that "islamophobia has become a real danger to the foundations of democratic order and the values of the European Union." (Osiewicz, 2017). Looking at the US, a similar trend is visible: the council on American-Islamic relations (CAIR) claims that islamophobia at the end of 2017 is worse than it has been directly after 9/11 (Buncombe, 2017). The hypotheses are developed in Chapter 4.3 and Chapter 4.4.

[2] Laouénan and Rathelot (2017) call the in- and out-group analysis in their study segregation analysis.

Authors	Guest/Hosts	Group	Finding
Edelman et al. (2017)	Guests	Blacks	Non-Black hosts charge approximately 12% more than Black hosts for the equivalent rental.
Cui et al. (2017)	Guests	Blacks	African-American sounding names are 19.2 percentage points less likely to be accepted than those with White-sounding names.
Edelman & Luca (2014)	Hosts	Blacks	Non-Black hosts charge approximately 12% more than Black hosts for the equivalent rental.
Cansoy & Schor (2017)	Hosts	Blacks	On average, in an All White census tract are 4 listings, that charge $120 each and have about 96 out of 100 rating. In contrast, on average in a Non-White tract are 2 listings, that charge $107 each and have about 94 out of 100 rating.
Mohammed (2017)	Hosts	Blacks	Narrowing of the racial bookings gap for hosts in NYC after design change of Airbnb website. However, gap still exists.
Wang et al. (2015)	Hosts	Asians	On average Asian hosts earn $90 less per week or 20% less than White hosts for similar rentals.
Kakar et al. (2017)	Hosts	Hispanics, Asians	On average, Hispanic and Asian hosts charge 8-10% lower prices relative to their White counterparts.
Laouénan & Rathelot (2017)	Hosts	Blacks, Muslims	Hosts from a minority ethnic group (Black and Arab/Muslim) charge 3.2% less than other hosts in the same cities (2.5 percentage points are statistical discrimination). No existence of in- and out-groups exist based on the criteria Muslim.

Table 3: Overview of all previous papers about ethnicity-based discrimination on Airbnb.

4.2 Background: Gender-based discrimination

For developing the gender-based hypotheses, we screened previous literature and considered global social facts that might influence discrimination. First, when screening the literature as done in Chapter 2, it shows that no evidence for gender discrimination has been found on Airbnb yet. Neither Edelman et al. (2017), who looked at Airbnb guests, nor Kakar et al. (2017), who investigated discrimination against Airbnb hosts, found significant price gaps.

Secondly, as previously stated, women are discriminated on a global scale. The Global Gender Gap Report revealed that women earn around $10,000 less per year (World Economic Forum, 2015) and the World Bank Group report showed, that women face legal discrimination in more than 100 countries (World Bank Group, 2018). The hypotheses are developed in Chapter 4.3 and Chapter 4.4.

4.3 Hypothesis 1: For testing price gaps

Concluding from Chapter 4.1, there are many ethnicity-based discrimination findings (identified price gaps), also one against Muslims, as well as recent social global developments with increased islamophobia. Therefore, regarding price gaps on Airbnb, we hypothesize the following:

Hypothesis 1.1

Airbnb hosts in Germany get discriminated by price based on their ethnicity (Muslim, Non-Muslim).

To conclude from Chapter 4.2, there is evidence that women are discriminated on a global scale. However, previous research did not confirm that discrimination exists on Airbnb. Since we are investigating the specific case of Airbnb, we base our hypothesis on the findings of past research:

Hypothesis 1.2

Airbnb hosts in Germany do not get discriminated by price based on their gender (male, female).

4.4 Hypothesis 2: For testing in- and out-groups

According to social identity theory, discrimination is explained by the existence of in- and out-groups. Therefore, if a price gap exists, then in- and out-groups should also exist. Since we hypothesised that a price gap exists for Muslim, but such a price gap does not exist for females, we hypothesize for in- and out- groups:

Hypothesis 2.1

In- and out-groups exist on Airbnb in Germany based on ethnicity (Muslim, Non-Muslim).

Hypothesis 2.2

In- and out-groups do not exist on Airbnb in Germany based on gender (male, female).

We want to mention that Laouénan and Rathelot (2017) have previously conducted a similar analysis and did not find the existence of in- and out-groups on Airbnb based on the criteria Muslim. However, their study only considered Berlin as the only German city. Chapter 7 explains how we aim to test the hypotheses and introduces the conditions for accepting or rejecting the hypotheses.

5. Methodology

Edmondson and McManus (2007) note that a methodological fit is important because if overlooked it can lead to inconsistencies. Therefore, in this chapter, we outline our fit and methodological reasoning based on the research onion by Saunders and Tosey (2013), which has been designed to guide researchers to an appropriate and coherent research design. As data collection and analysis take a major part of our study, these parts from the most inner ring of the research onion have their own chapters: data collection is described in Chapter 6 and data analysis in Chapter 7. Figure 4 gives an overview of our methodological choices, which are further described in the subsequent subchapters.

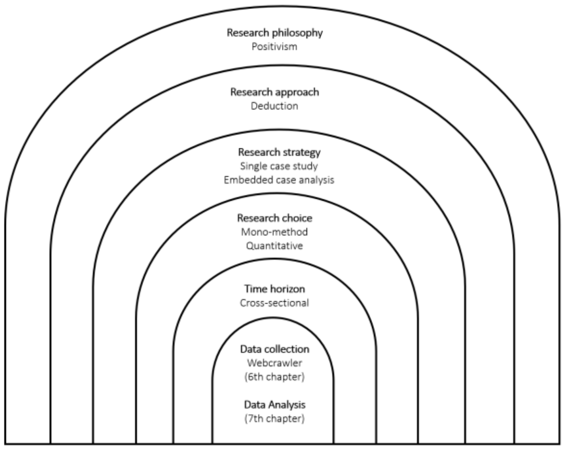

Figure 4: The research onion based on Saunders and Tosey (2013).

5.1 Research philosophy

Research philosophy is concerned with the development of knowledge and the nature of knowledge (Saunders, Lewis & Thornhill, 2007). Moreover, epistemology concerns what constitutes acceptable knowledge in a research study (Saunders et al., 2007). We decided for the principles of positivism as we prefer to work with an observable social reality and that the end product of research can be law-like generalisations similar to those produced by physical and natural scientists (Remenyi, Williams, Money & Swartz, 1998). Furthermore, in this thesis we make use of existing theories to develop hypotheses, which we test afterwards. We are convinced that we undertake research in a value-free way as the data we work with are facts we do not influence. Therefore, in our eyes the way we affect or are affected by the subject of matter is low, which is a characteristic of positivism according to Remenyi et al. (1998). Lastly, we work with a highly structured methodology, which is further outlined in this chapter, in order to facilitate replication (Gill & Johnson, 2002).

5.2 Research approach

Regarding our research approach, we follow the process of deduction, which is illustrated in Figure 5. The right side shows the process of deduction according to Bryman and Bell (2003). The left side puts the structure of our thesis in comparison. We started with a theoretical framework in Chapter 3, followed by hypotheses development in Chapter 4. Chapter 6 fulfills the third step in the process of deduction, by describing the data collection process. Subsequently, Chapter 8 presents our empirical results and accepts or rejects the hypotheses, which is the fourth step in the process of Bryman and Bell (2003). Lastly, we discuss the theory based on our results in Chapter 9.

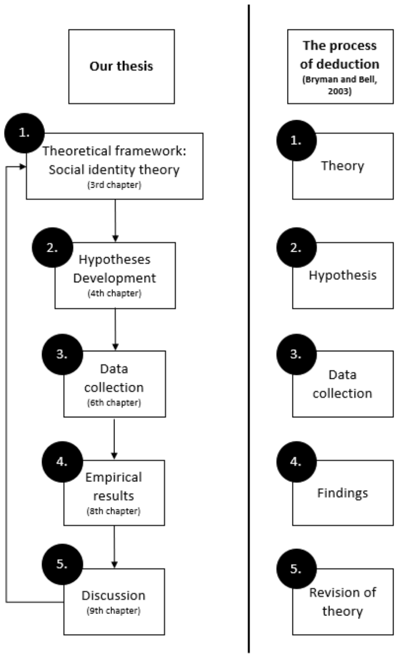

Figure 5: Deduction process based on Bryman and Bell (2003).

5.3 Research strategy

We chose a case study strategy as we investigate a particular phenomenon with its real life context involving an empirical investigation (Robson, 2002). Our particular phenomenon is discrimination and we investigate it empirically with an OLS regression. A real life context is given as we collect data directly from Airbnb with a web crawler that does not interfere interactions on the website (the web crawler is further described in Chapter 6). As we focus on one country, Germany, we conduct a single case study according to the distinction of case studies by Yin (2003). We further conduct an embedded case analysis as sub-units within the organization are the unit of analysis (behaviour of guests) and not the Airbnb organization as a whole (Yin, 2003).

5.4 Research choice

Considering that we study discrimination, we chose a quantitative mono-method as it is difficult to measure discrimination qualitatively: subjects sometimes discriminate unconsciously or might not be willing to confess their discriminatory behaviour in a study (Dovidio & Gaertner, 2000). For that purpose, we decided for a quantitative method. Moreover, we decided for a data collection process that does not influence the behaviour of subjects on Airbnb. Our data collection process is further explained in Chapter 6.

5.5 Time horizon

Due to technical feasibility, we decided for a cross-sectional design. Longitudinal case studies are difficult to conduct when using a web crawler. Every time the design of the website changes, the web crawler needs to get manually updated. Therefore, it is difficult to collect high quality data over a longer period with a web crawler. The issues are further discussed in Chapter 6.5.

6 Data collection

Before testing the existence of price gaps as well as the existence of in- and out-groups, we had to decide which data points we collect. The selection process for our data is discussed in Chapter 6.1. Subsequently, our data collection tool, the web crawler, is described in Chapter 6.2, followed by the crawling process (6.3), the filters we applied on the dataset (6.4), as well as the challenges we faced and data quality checks (6.5). As mentioned in Chapter 5.5, our study is cross-sectional. We collected the data in March 2018 within one week.

6.1 Selection of collected data

Within the decision process which data to collect, our intention was to include variables from all categories that influence prices on Airbnb. For that purpose, we orientated towards previous discrimination research. Table 4 gives an overview of variables used by studies that investigated discrimination against hosts on Airbnb. Moreover, we considered the study from Teubner, Hawlitschek and Dann (2017) as a source of inspiration because it contained further variables beyond the ones used in previous discrimination research. The last row shows our choice of variables which is a mix of previous papers. Our choices are motivated in detail below.

Mohammed (2017)	Independent variables • Race	Listing characteristics • Type of listing • # of bedrooms • # guests					Occupancy • Bookings per week • Listed days per week	
Laouénan & Rathelot (2017)	Ethnicity	Property characteristics • # of bedrooms • Terrace or balcony • Couch/Airbed/Sofa			City characteristics	Neighbourhood characteristics		
Edelman & Luca (2014)	Race	Characteristics of property • # of bedrooms • Has LinkedIn / Facebook • Picture quality	Quality of property • Scores for different ratings					
Cansoy & Schor (2017)		Listing characteristics • # of amenities • Room type • # of guests			Regional characteristics • Total population	Census tract characteristics • Gini coefficient • Median housing cost • % renter		
Wang et al. (2015)	Race	Listing characteristics • # of bedrooms • # of bathrooms • Occupancy rate						
Kakar et al. (2017)	Host characteristics • Race • Gender	Rental listing features • Type of listing • Superhost • Has Facebook /LinkedIn	User reviews • # of reviews • Review scores for different categories			Neighbourhood characteristics • Median income • % White • % Asian	Occupancy • Occupancy rate	
Teubner et al. (2017)	Personal attributes • Profile picture • Ethnicity • Gender	Apartment attributes • # of guests • Type of accommodation • Distance to the city center	Reputation attributes • Average rating • ID verification • # of photos • Duration of memberhip • …	Convenience attributes • Instant booking • Deposit requirement • Cancellation strictness	City attributes • General rent price level			
Our thesis	Independent variables • Gender (male, female) • Ethnicity (Muslim, Non-Muslim)	Listing characteristics • # of guests • # of bedrooms • # of bathrooms • …		Host characteristics • Cancellation strictness • # of reviews • Membership months • …	Location characteristics • Price per sqm • Walkability Score		Occupancy • 1 months availability ratio • 2 months availability ratio • 3 motnhs availability ratio	Price variables • Cleaning fee • Weekly discount • Monthly discount • …

Table 4: Overview of data collected in past research in which price was used as a dependent variable and our choice of data collection.

First, the category ‘Independent variables’ contains the variables of interest in our study, which are gender (male, female) and ethnicity (Muslim, Non-Muslim).
Second, we decided for the category ‘Listing characteristics’ since past research has shown that these variables have a significant impact on price.
Third, we included the category ‘Host characteristics’. For technical reasons we were not able to collect the rating scores. However, we got inspired by Teubner et al. (2017) and included variables such as cancellation strictness, the number of reviews or the host’s membership months.
Fourth, as done by Mohammed (2017) and Kakar et al. (2017), we collected data about the occupancy of the listing, we called the variable *availability ratio*.
Fifth, we added the category ‘Location characteristics’ similar to Laouénan and Rathelot (2017), Cansoy and Schor (2017), Kakar et al. (2017) and Teubner et al. (2017). However, we used more granular data as previous research as we included walkability ratings and prices per sqm based on the longitude and latitude of listings. In that way we followed the call of Kakar et al. (2017) who demanded an expansion of control variables.
Sixth, within the category ‘Price variables’ we collected which price mechanisms hosts used to set their prices. In general, there are three different methods how prices can be set on Airbnb: default, custom and demand-based pricing. Default pricing means that hosts set a default price that is used as the price per night for all the days in their calendar. When hosts chose custom pricing, they can select individual days or time periods for which they set a certain price. In November 2015, Airbnb added demand-based pricing as a third option (Bell, 2015; Hook, 2015). Demand-based pricing consists of an algorithm that determines the rent for every day based on the demand in the area of the listing. While previous research has not distinguished between the different price mechanisms, we control for the three different types, because the way the price is set might have a significant impact on the price.

6.2 The web crawler

We used a web crawler in order to obtain the data for the Airbnb listings. A web crawler is a software program that automatically scans a webpage for certain information by using the source code of the webpage. The upper side of Figure 6 illustrates an example of a source code, whereas the lower side shows how a common web browser would visualize the corresponding source code. In more detail, the web crawler opens the URL of a webpage, reads in the source code of the webpage, and then scans the source code for certain keywords. In the example of Figure 6, the web crawler would search for the key word “bathroom_label” and then look up the corresponding information “1 bath” (see highlighted line). In the final step, the web crawler saves the information in a local database. We programmed such a web crawler for the specific use to scan the webpages of all Airbnb listings for the given cities. The web crawler was programmed in Java and contains more than 2,000 lines of code. Using a web crawler to obtain data from Airbnb is a common method in discrimination literature. Table 5 gives a list of authors who have used this method before in the context of Airbnb.

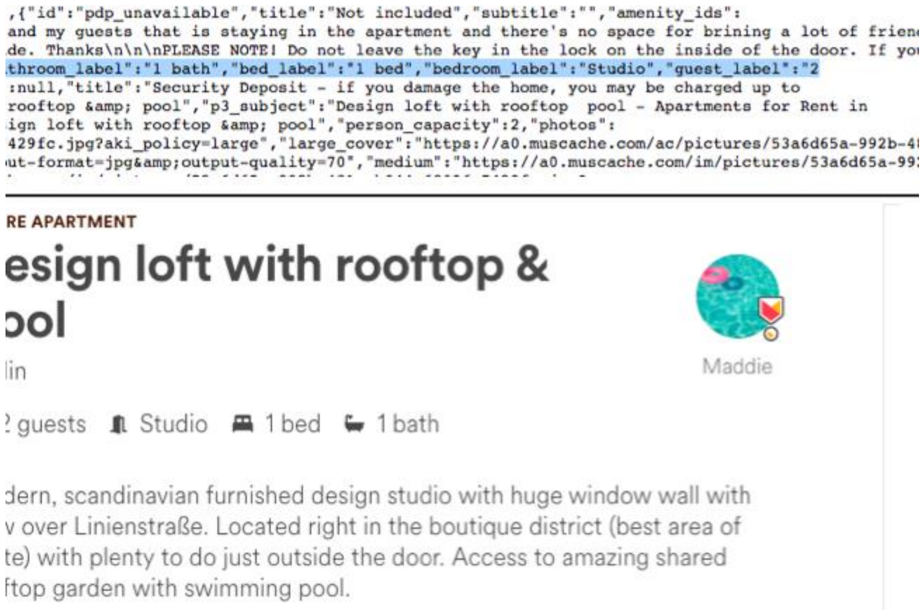

Figure 6: The upper part shows a snippet of the source code of the Airbnb website. The lower part shows how a common web browser visualizes this part.

Authors	Title
Wang et al. (2015)	The Model Minority? Not on Airbnb.com: A Hedonic Pricing Model to Quantify Racial Bias against Asian Americans.
Lauénan & Rathelot (2017)	Ethnic Discrimination on an Online Marketplace of Vacation Rental
Cui et al. (2017)	Discrimination with Incomplete Information in the Sharing Economy: Evidence from Field Experiments on Airbnb
Hannák et al. (2017)	Bias in Online Freelance Marketplaces: Evidence from TaskRabbit and Fiverr
Edelman & Luca (2014)	Digital discrimination: The case of Airbnb.com
Cansoy & Schor (2017)	Who gets to share in the "sharing economy"? Racial discrimination in Participation, Pricing and Ratings on Airbnb
Kakar et al. (2017)	The Visible Host: Does race guide Airbnb rental rates in San Francisco?
Mohammed (2017)	Designing for Racial Impartiality: The Impact of Relocating Host Photos on the Airbnb Website

Table 5: List of studies that also used a web crawler.

6.3 The crawling process

We split the data collection process into two steps, resulting in two datasets. Chapter 6.3.1 explains the crawling process in which we obtained the Dataset 1 to test for price discrimination. In a second step, we took a random sample out of Dataset 1 and executed additional crawling in order to obtain the Dataset 2 for testing in- and out-groups. The process how we obtained Dataset 2 is explained in Chapter 6.3.2.

6.3.1 Crawling process for Dataset 1 (testing price discrimination)

This subchapter explains how we collected the dataset that we used for testing price discrimination (Dataset 1). We divided the process into two steps as illustrated in Figure 7.

The purpose of the first step was to obtain an initial dataset with information about the Airbnb listings. For each Airbnb listing in the 82 largest cities of Germany[3], we collected a variety of variables, such as *price*, *host name*, *rating*, *reviews*, *guest names*, etc. A list of all variables is provided in Chapter 7.3. In this step we collected data from 76,061 Airbnb listings.

In the second step we used external APIs and additional web crawling in order to complement the initial dataset with more variables. Through this process we added four variables: *host gender*, *host ethnicity*, *walkability score*, *sqm price*. After these two processes, Dataset 1 was complete.

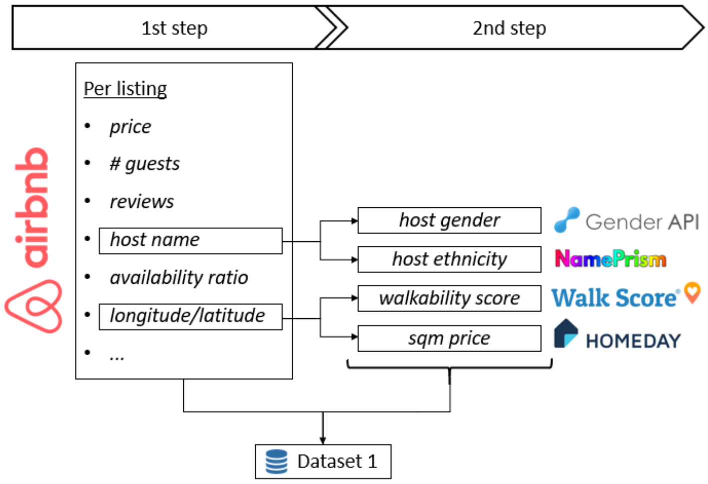

Figure 7: Data collection process for Dataset 1.

Host gender is divided into the categories 'male' and 'female'. We derived gender by using the commercial API "Gender API". The API uses the host's name (which was collected in the first step) as an input and gives as an output the gender as well as a probability value which measures to which extend the API thinks it determined the correct gender.

Host ethnicity is determined in two ways: through the open API "Name Prism" and through a list of Arabic, Muslim names. Similar to the gender API, Name Prism determines *host ethnicity* based on the host's name. If the API determines a name as Muslim with at least 90% probability, then this host is marked as Muslim in the dataset. Additionally, if a host name appears in the list of Muslim names, then this host is also marked as Muslim (as also done by Laouénan and Rathelot, 2017). The list of Muslim names was derived from the websites vorname.com, babynames.net, as well as wikipedia[4]. All other host names were marked as Non-Muslim.

Walkability score is a score for the attractiveness of a specific location in a city. The score is determined by the website walkscore.com on a scale from 0 to 100 and measures how easy it is to walk in an area to restaurants, bars, parks, etc. For instance, an area with a score between 0 and 24 is Car Dependent and a score between 90 and 100 is Walker's Paradise (Figure 8). For determining the score, seven subscores are generated for categories ranging from 'Dining & Drinking' to 'Shopping' to 'Parks' (Figure

[3] A list of all 82 cities is provided in Appendix D.

[4] https://de.wikipedia.org/wiki/Liste_t%C3%BCrkischer_Vornamen

8). We programmed a web crawler that opened the webpage of walkscore.com, put in the latitudinal and longitudinal coordinates of each Airbnb listing (which were collected in the first step), and collected the respective *walkability score*.

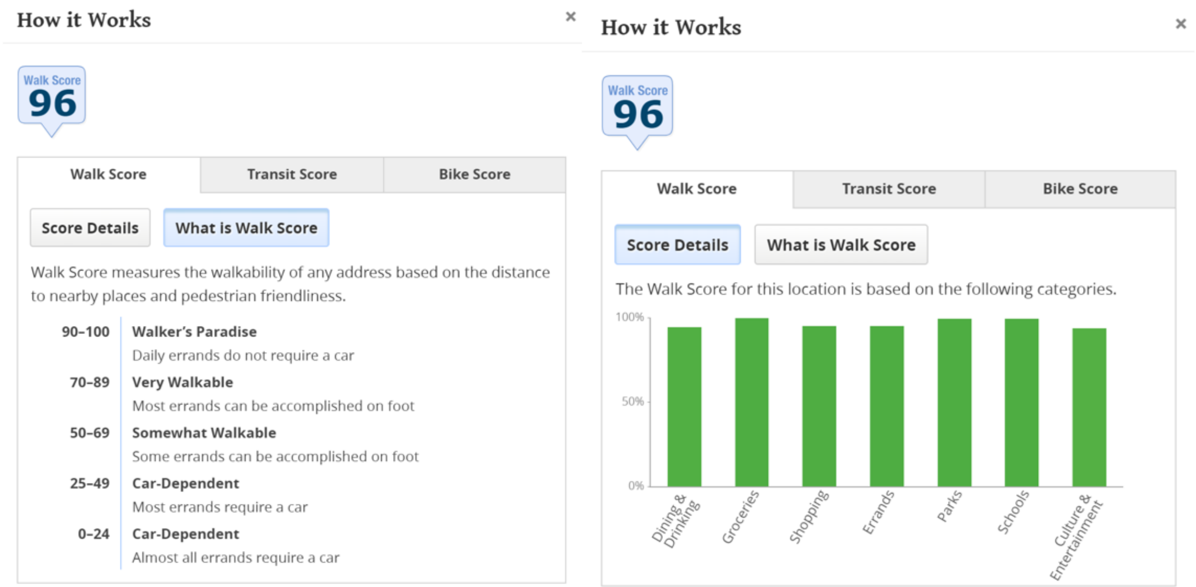

Figure 8: Screenshots from walkscore.com explaining how the walkability score works.

Sqm price is the average bying price per square meter for a specific location in a city. The value is determined by web crawling homeday.de. As seen in Figure 9, the website uses the street name as an input and gives as an output the average buying price per square meter for an apartment in that street. Since we only had the latitudinal and longitudinal coordinates of each Airbnb listing, we first had to use the Google Maps API in order to geocode the coordinates into the corresponding street names. Once we had the street name for every Airbnb listing, we could use a web crawler to open the webpage of homeday.de, put in the street name, and collect the respective *sqm price*.

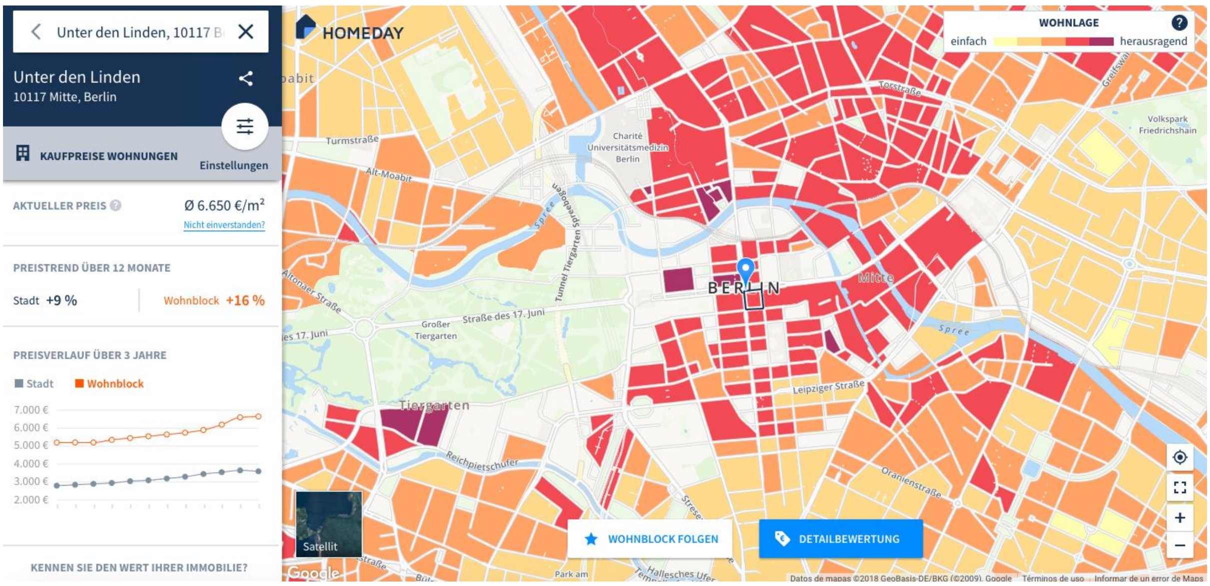

Figure 9: Screenshot of the website homeday.de showing square meter prices of apartments in Berlin.

6.3.2 Crawling process for Dataset 2 (testing in- and out-groups)

After we had collected the dataset for testing price discrimination (Dataset 1), we collected the dataset for testing in- and out-groups (Dataset 2). We divided that additional crawling process in three steps as illustrated in Figure 10.

In the first step, we selected randomly 500 listings from Dataset 1, after it had been filtered (the filter process is described in Chapter 6.4). We conducted the random selection process by generating 500 times a random number between 1 and 27,141 and then, for each number generated, we selected the respective listing in the dataset. We had to take random samples instead of using the whole dataset for practical reasons. With our random sample of 500 listings, we already had to identify the gender and ethnicity of over 10,000 guests. Using the whole dataset would have been too time-consuming and costly.

In the second step, we used the reviews that we had collected for each listing to derive the guests' names that had stayed at the listing. With the names, we then determined the gender and ethnicity for each guest. This process was done once again with GenderAPI and NamePrism (see Chapter 6.3.1). At the end of this step, for each of the 500 listings we had collected the ethnicity and gender of all guests.

In the third step, we calculated *%muslim guests* and *%female guests* for each listing. *%muslim guests* is simply calculated per listing as the sum of the number of Muslim guests divided by the total number of guests. *%female guests* was also calculated as the proportion of females to all guests of one listing. After the three steps, we had completed the collection for Dataset 2.

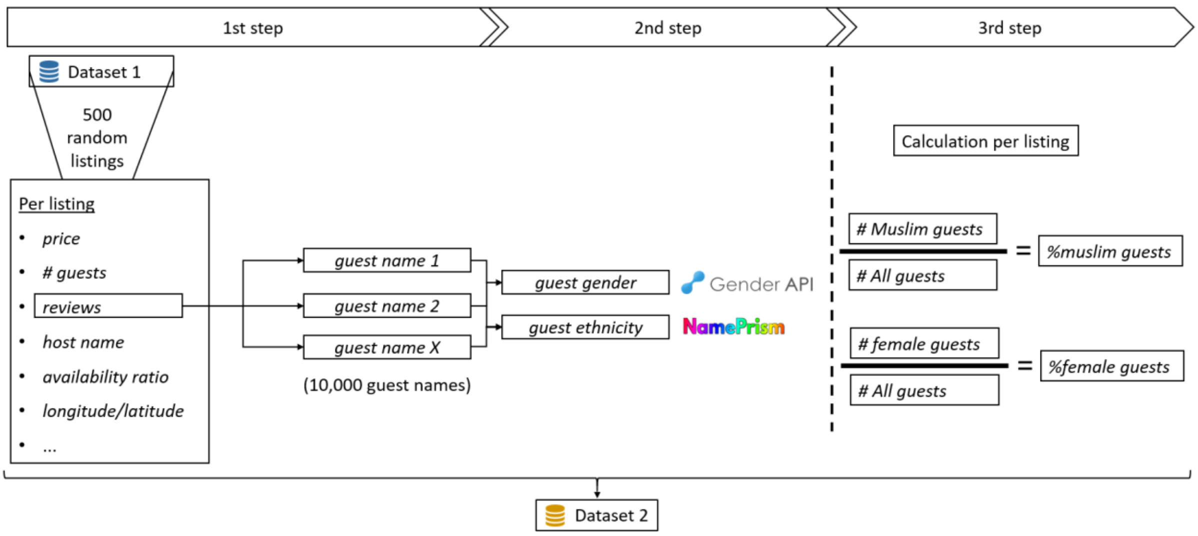

Figure 10: Data collection process for Dataset 2.

6.4 Filter

As briefly outlined, we filtered Dataset 1 in order to assure high data quality. Figure 11 gives an overview of how we filtered the dataset. First, we removed all listings in which *availability ratio* was 0% for the next three months. *Availability ratio* was taken from the listing's calendar and measures in percentage how many days the listing is available to get booked for a given month. There are two reasons why a listing is not available to get booked for a given day. First, the host already has a booking for this day and Airbnb automatically blocked that day in the calendar. Second, the host does not want to rent the listing on that particular day and blocked it by himself/herself. However, if *availability ratio* is 0% for the next three months, that means that this listing cannot be booked for even a single day within the next three months. It seems unrealistic that a listing is blocked continuously due to bookings. Instead, we assume that these days were blocked by the host himself/herself because the listing is inactive, meaning that the host does not want to rent out the listing for that months. Indeed, it could be that the listing is inactive since months, if not years. Consequently, the price of the listing would be outdated and falsify the regression with *price* as the dependent variable. Therefore, we excluded all listings with a*vailability ratio* equal to 0% for the next three months. This filter reduced the initial size of 76,061 listings to 38,977 listings.

Secondly, since the host's name is the only input, the APIs could mistakenly determine *gender* in wrong ways. For example, Andrea is a female name in Germany whereas it is a male name in Italy. Therefore, we removed all listings for which the gender detection API determined *gender* with a probability less than 90%. In this way, we can assure high validity that the determined gender in the dataset matches the host's real gender. This threshold is in line with Mohammed (2017), who rejected all listings in which the host's ethnicity could not be determined with a probability of at least 90%. Moreover, sometimes two or more people rent out a listing together. In that case, *host name* consists of two or more names. We excluded those listings in order to only consider listing that are rented out by one person. Through this filter, the sample size further decreased from 38,977 to 34,368 listings.

In a third step, we excluded all listings for which the website homeday.de could not provide a value for *sqm price*, mainly because those listings are located to remotely that no data about square meter prices are available. We applied the same filter for listings for which *walkability score* could not be determined. The number of listings then reduced from 34,368 to 33,701 listings.

In a last step, we removed listings for which hosts did not set values for the variables *bedrooms* or *bathrooms*. As we do not have a numeric value for those variables, we could not include them in the regression as numeric variables. The only way to include them would be as factor variables, but then the regression would build for each observed value of the variable a separated dummy variable. For instance, #beds has in total 22 different observation values and, hence, the regression would create 21 dummy variables (the first observation value is set as a default value and, hence, for the remaining 21 observation values the regression builds for each one a separated dummy variable). Consequently, the interpretation would be difficult and, therefore, we removed those listings. Through the last filter, we reduce N from 33,701 to the final number of 27,141 listings.

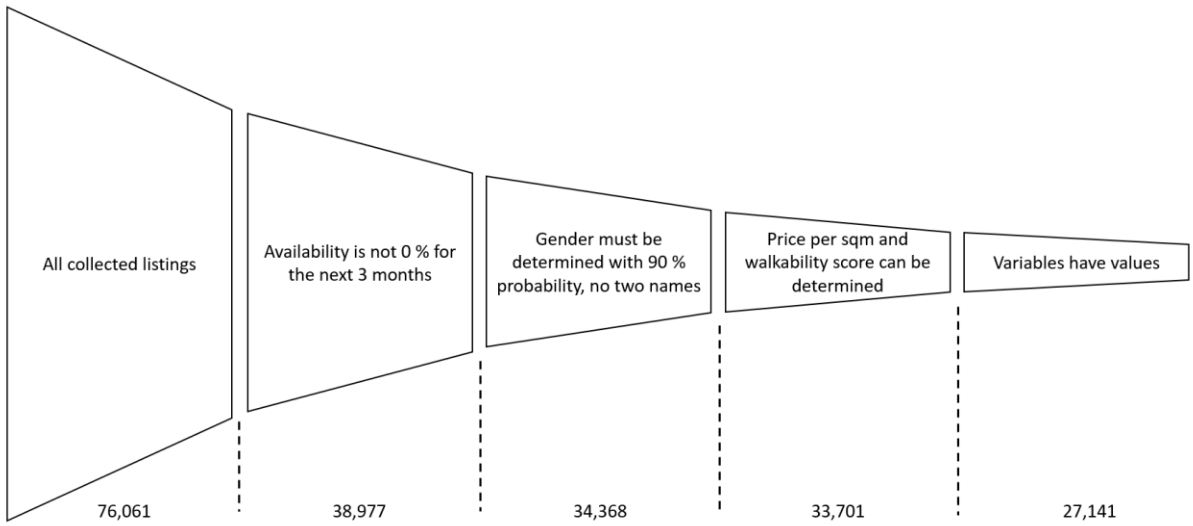

Figure 11: Filtering process of all collected listings for Dataset 1.

6.5 Challenges and data quality checks

When coding the crawler we faced two main challenges: one individual challenge related to our study and one general challenge due to the nature of the web crawler. First, in the specific context of our study, Airbnb shows only a limited number of listings when searching for listings in a specific city. For example, when looking for listings in Berlin, Airbnb only displays 300 listings, however, there are around 9,000 listings in Berlin. Therefore, if the web crawler would only search for listings by city, there might be the risk that not all listings are collected. Therefore, we added three more search variables to the city name itself in order to narrow down the search query: price range, listing type, and geographical zone within the city (we geographically split large cities such as Berlin in 64 quadrants called 'zones'). The whole crawling process then consisted by four loops. For example, the web crawler would first perform a search query with the following search filters for the first city:

- price range: $0-1
- listing type: shared room
- geographic zone: 1

In the second search query the web crawler would have the same search filters, but it would look for the second geographic zone and so on. When all geographical zones are completed, the web crawler would change listing type to only private rooms and start from the first geographical zone. When all listing types are completed, the web crawler would increase the price range to $1-2 and so on. Finally, if all price ranges are completed, the web crawler would continue with the second city and so on until all 82 cities are crawled[5]. Table 6 gives an example of the four-loop crawling process. Since we crawled in total 82 cities for which each of them we narrowed down the search query to 100 different price ranges, 3 different listing types and 64 different geographical zones, our web crawler performed in total over 1,500,000 search queries.

City	Price range	Listing type	Zone
Berlin	$0-1	shared room	1
Berlin	$0-1	shared room	2
Berlin	$0-1	shared room	...
Berlin	$0-1	shared room	64
Berlin	$0-1	private room	1
Berlin	$0-1	private room	...
Berlin	$0-1	private room	64
Berlin	$0-1	whole apartment	...
Berlin	$1-2	shared room	1
Berlin	...	...	...
Hamburg	$0-1	shared room	1
...	...	...	...

Table 6: Example showing the loop process of the search queries the web crawler performed.

Second, in general if a web crawler is not programmed correctly and has malfunctions, there might be the probability that the crawler is collecting wrong data. Web crawlers are especially vulnerable to changes of the website design (Gelman, 2016). For example, if Airbnb changes the design of its website just right after the crawler was programmed, the crawler might collect wrong values.

To be sure that a data set collected at a single point in time is not flawed, it is necessary to check the quality of the dataset after the data collection process. For that purpose, we conducted quality checks

[5] A list of all 82 cities is provided in Appendix D.

in two ways. First, we made a dimension check of each variable. For instance, the variable *price* should only have numeric values and the variable *listing type* only “shared room”, “private room”, and “whole apartment”. Using the dimension check we can assure that each variable only contains values that make sense. Second, we took random samples from our dataset and manually checked the values of the variables on the Airbnb website. We checked all collected variables of 200 listings randomly sampled from all 82 German cities. For both tests we did not find any wrong values, concluding that the crawler most likely worked without errors.

7. Dataset Analysis

This chapter explains the analysis of our datasets. Chapter 7.1 explains the regression design for testing price gaps (Hypotheses 1.1 and 1.2) and Chapter 7.2 explains the regression design for testing the existence of in- and out-groups (Hypotheses 2.1 and 2.2). Subsequently, the used regression variables are introduced (7.3) as well as a summary statistics is given (7.4).

7.1 Design for Regression A (testing price gaps)

In order to test Hypotheses 1.1 and 1.2, to which extent Muslims/Non-Muslims and males/females get price discriminated on Airbnb, we ran a linear regression. A regression is especially useful in our case, since we want to isolate the effect of ethnicity and gender. In fact, as seen in Table 2, the majority of researchers who investigated discrimination on Airbnb also used linear regressions. In our regression *price,* the natural logarithm of the listing's average price per night for the next three months, is the dependent variable. In Chapter 7.3.1 we explain in more detail the variable *price* and why we used its natural logarithm. The independent variables are *muslim* and *female* (see Chapter 7.3.2). Both variables are binary coded and have the value "1" if the host is Muslim or female, respectively. In addition, we control for a variety of other variables, such as *guests*, *bedrooms*, *walkability score*, etc. (see Chapter 7.3.3). By doing so we can isolate the effect of the independent variables, *muslim* and *female*, on the dependent variable *price*. In other words, we test the effect on the listings' price in case that the host is Muslim or female. In this thesis, we refer to this regression as 'Regression A'.
Similar to previous research (Wang et. al, 2015), we assume that discrimination exists if the independent variables, *muslim* and *female*, are statistically significant. In line with past studies, we define a variable as statistically significant when its p-Value is lower than 5% and vice versa. Therefore, if the hypothesis is that discrimination exists, we would accept the hypothesis if the p-Value of the corresponding independent variable is lower than 5%. In the contrary, if the hypothesis is that discrimination does not exist, we would accept the hypothesis if the p-Value is higher than 5%.
Therefore, we accept hypotheses 1.1 if *muslim* is statistically significant with a p-Value less than 5%. Contrary, we accept Hypothesis 1.2 if *female* is statistically significant with a p-Value higher than 5%.

Figure 12 sums up the whole process. We tested for price gaps based on ethnicity (Muslim, Non-Muslim) and gender (male, female), Hypothesis 1.1 and 1.2, respectively. Using Dataset 1, we ran Regression A, which uses *price* as the dependent variable and *muslim* and *female* as independent variables. Finally, we accepted Hypothesis 1.1 if the p-Value of *muslim* was lower than 5% and we accept Hypothesis 1.2 if the p-Value of *female* was higher than 5%.

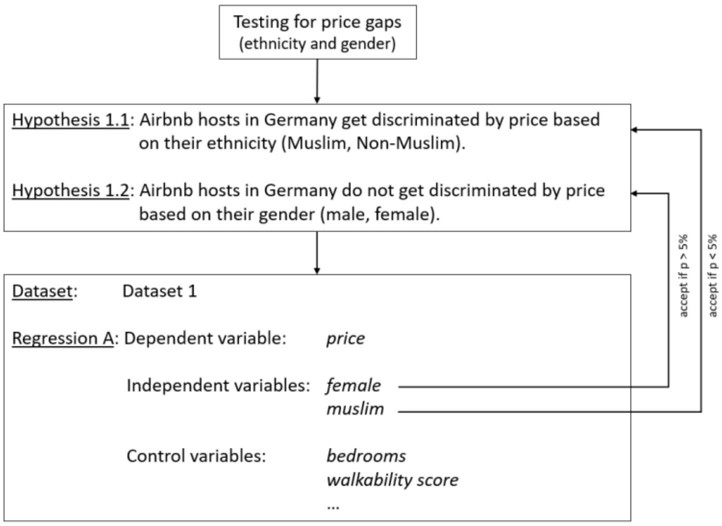

Figure 12: Overview of the connections among testing for price gaps, Hypothesis 1.1 and 1.2, Dataset 1, and Regression A.

Regression A can be described mathematically in the following equation in which y_1 is the price vector, X_1 is the matrix of all the independent and control variables, β_1 is the coefficient vector, and u_1 is the error term vector. Consequently, y_1 is a N-dimensional column vector, X_1 is a N × (K + 1) matrix, β_1 is a (K +1)-dimensional column vector, and u_1 is a N-dimensional column vector. As seen in Chapter 6.4, in our final regression model, the sample size is 27,141 and the number of independent and control variables is 26. Hence, N equals 27,141 and K equals 26. Hence, Equation A is:

(A) $y_1 = X_1\beta_1 + u_1$

All past studies that investigated a price gap used an ordinary least square (OLS) regression (Mohammed, 2017; Laouénan & Rathelot, 2017; Edelman & Luca, 2014; Cansoy & Schor, 2017; Wang et al., 2017; Kakar et al., 2017; Teubner et al., 2017). Therefore, we first checked whether an OLS regression is also applicable in our case. In order to do so, we tested whether the assumptions underlying an OLS regression hold true in our specific case. One of the main assumptions is that the error terms fulfil the zero conditional mean assumption, meaning that the error terms' expected value is zero (Wooldridge, 2013). To put it in other words, the error terms do not depend on the independent variables. In order to check for potential heteroskedasticity, we plotted the residuals predicted values. As seen in Figure 16 in Chapter 8.1.2, there was no significant systematic change of the residuals as they are all equally spread. Therefore, we concluded that the assumption holds true. Moreover, another assumption is that multicollinearity does not exist, meaning that there is no linear relationship among the independent variables. We checked for multicollinearity by analysing the correlation matrix, in which we did not find any significant relationships among the independent variables. In conclusion, the main assumptions of an OLS regression hold true and, therefore, we decided to run an OLS regression.

7.2 Design for Regressions B and C (testing in- and out-groups)

In order to test Hypothesis 2.1 and 2.2, the existence of in- and out-groups concerning ethnicity and gender, we ran two regressions: one for ethnicity and one for gender. In our thesis, we refer to those regressions as Regression B and Regression C, respectively. In Regression B we use *%muslim guests* as

the dependent variable. That variable states how much percent of the host's guests are muslim. The independent variable is *muslim* and we control for the same variables as in Regression A (see Chapter 7.1). In other words, we test whether the Muslim ethnicity of the host has an effect on how many Muslim guests he/she has. If we find a positive effect, then we can conclude that Muslim guests and Muslim hosts prefer to stay with each other and, therefore, form an in-group.
Similarly, in 'Regression C' we use *%female guests* as the dependent variable and *female* as the independent variable while controlling for the same variables as in Regression A. Once again, if we find a positive effect of *female* on *%female guests*, then we can conclude that females prefer to stay among each other and, hence, that an in-group exists.
We accept Hypothesis 2.1 if *muslim* is statistically significant with a p-Value lower than 5%. In the contrary, we accept Hypothesis 2.2 if *female* is not statistically significant with a p-Value higher than 5%.

Figure 13 sums up the whole process. We tested for the existence of in- and out-groups based on ethnicity (Muslim, Non-Muslim) and gender (male, female), which resulted in Hypothesis 2.1 and 2.2, respectively. Using Dataset 2, we ran two regressions: Regression B (with *%muslim guests* and *muslim*) and Regression C (with *%female guests* and *female*). Finally, we accepted Hypothesis 2.1 if the p-Value of *muslim* is lower than 5% and we accepted Hypothesis 2.2 if the p-Value of *female* was higher than 5%.

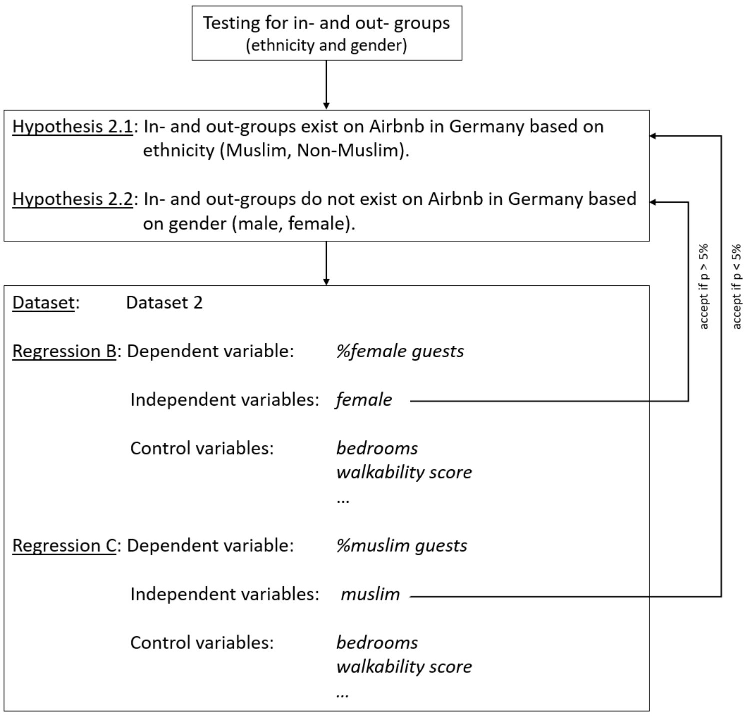

Figure 13: Overview of the connections among testing for in- and out-groups, Hypothesis 2.1 and 2.2, Dataset 2, and Regression B and C.

Since we have two regressions for testing in- and out-groups with different dependent variables, we also have two different regression equations. Equation B refers to the regression in which *%muslim guests* is the dependent and *muslim* the independent variables, whereas Equation C refers to the one with *%female guests* and *female*.

(B) $y_{2,1} = X_{2,1}\beta_{2,1} + u_{2,1}$
(C) $y_{2,2} = X_{2,2}\beta_{2,2} + u_{2,2}$

As stated in Chapter 7.1, the assumptions of an OLS regression hold true in our case. Moreover, Laouénan and Rathelot (2017) also used an OLS regression to test for in- and out-groups. Therefore, similar to the regression for testing price gaps, we used an OLS regression in order to test for in- and out-groups.

7.3 Regression variables

This chapter introduces the regression variables, which are split into the dependent variables (7.3.1), the independent variables (7.3.2) and control variables (7.3.3). As mentioned above, we ran in total three regressions (A, B, and C). The control variables are the same in all three regressions, but the dependent and independent variables differ among the three regressions.

7.3.1 Dependent variables

Dependent variable: Regression A
In Regression A, in which we test for price gaps, we used *price* as the dependent variable, which is the natural logarithm of the average listing price per night of all prices in the next three months. We used the natural logarithm primarily for two reasons.
First, when looking at the residuals vs. fitted plot of the average price itself (that is without taking the logarithm), we can see that the plot does not seem well-behaved (see left-side of Figure 14). The residuals do not “bounce randomly” around the zero line. Indeed, it seems like with increasing fitted values, residuals tend to be located rather above than below the zero line. In contrast, when using the logarithm of price, the residuals vs. fitted plot seems more well-behaved (see right-side of Figure 14). Now, the residuals roughly form a horizontal band around the zero line, suggesting that the variances of the error terms are equal. Second, when analysing the distribution of the average price itself, one can see that *price* is heavily skewed as it has a long-tail (see left-side of Figure 15). In contrast, *price* is more normal distributed (see right-side of Figure 15). For those two reasons we decided to use the logarithm of the price.

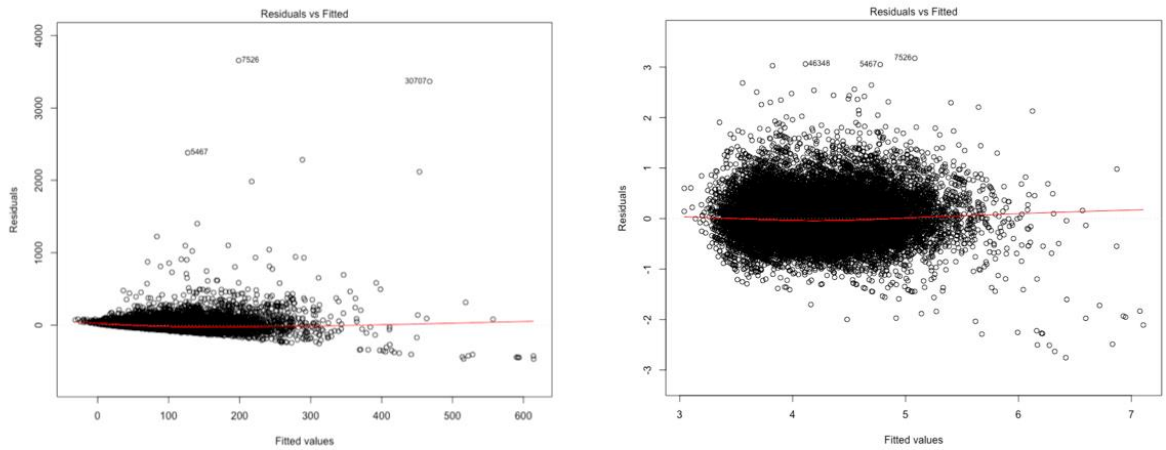

Figure 14: Residuals vs. Fitted plots for the regression with the price itself (left-side) and the logarithm of the price (right-side).

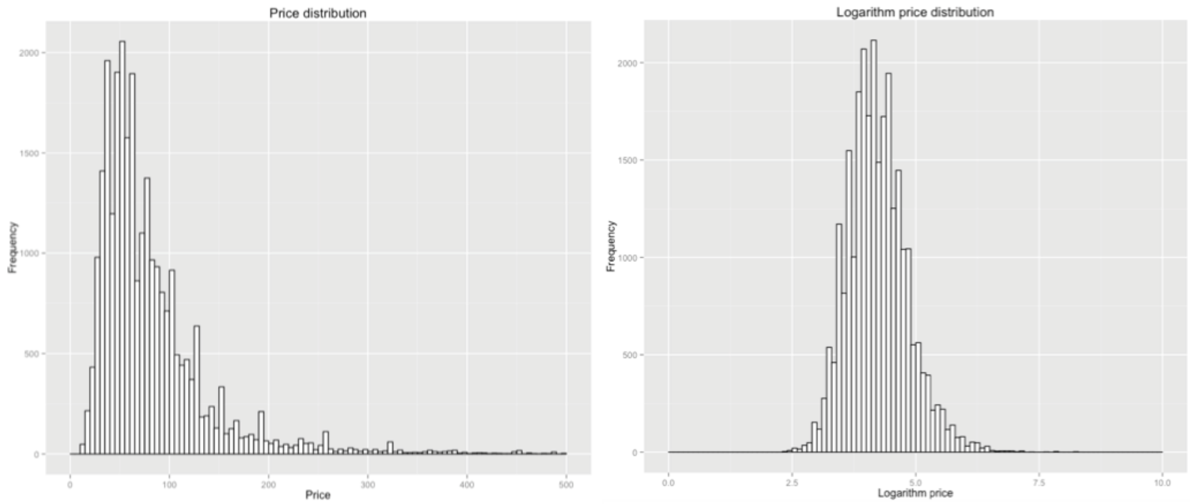

Figure 15: Histogram plots of the price itself (left-side) and the logarithm of the price (right-side).

<u>Dependent variables: Regressions B and C</u>

In order to test for the existence of in- and out-groups, we ran in total two regressions (Regressions B and C) with different dependent variables: *%muslim guests* and *%female guests*. As already mentioned in Chapter 6.3.2, *%muslim guests* and *%female guests* state how much percent of a listing's guests are Muslim and female, respectively. Table 7 summarizes all dependent variables.

Variable	Dimension	Regression	Description
price	numeric	A	Natural logarithm of the average listing price per night in the next three months.
%muslim guests	%	B	Percentage of how many guests of a listing are Muslim.
%female guests	%	C	Percentage of how many guests of a listing are female.

Table 7: Overview of the dependent variables.

7.3.2 Independent variables

The independent variables are the variables for which we want to investigate the impact on the dependent variables: gender and ethnicity. We coded a binary dummy variable for gender and ethnicity: *female* and *muslim*. *Female* has the value "1" if the host is female. Similarly, Muslim has the value "1" if the host is presumably Muslim. Regression A uses both variables, *female* and *muslim*, whereas Regression B only *muslim* and Regression C only *female*. Table 8 gives an overview of the two independent variables included in the study.

Variable	Dimension	Regression	Description
female	binary	A, C	Gender of the host: '1' if the host is female and '0' if the host is male.
muslim	binary	A, B	Ethnicity of the host: '1' if the host is Muslim and '1' if the host is Non-Muslim

Table 8: Overview of the independent variables.

7.3.3 Control variables

The control variables are the variables that we use to isolate the effect of the independent variables (*gender* and *ethnicity*) on the dependent variable (*price*). We split the control variables in the four groups that were outlined in Chapter 6.1: price variables, listing characteristics, location characteristics and host characteristics. The control variables are the same in all three regressions (A, B, and C). Table 9 gives an overview of the control variables. How the details are displayed on the Airbnb website can be seen in Appendix B.

Variable	Dimension	Description
Price variables		
Cleaning fee	$	A one-time fee that is charged for cleaning the apartment.
Weekly discount	%	The percentage of discount per week if guests book for one week.
Monthly discount	%	The percentage of discount per month if guests book for one month.
Custom pricing	%	For how many days of the next three months the price was set through custom pricing.
Demand pricing	%	For how many days of the next three months the price was set through demand pricing.
Default pricing	%	For how many days of the next three months the price was set through default pricing.
Listing characteristics		
Guests	numeric	The maximum number of guests allowed.
Bedrooms	numeric	The number of bedrooms offered.
Bathrooms	numeric	The number of bathrooms offered.
Listing type	factorial	The type of the listing: shared room, private room or whole apartment.
Luxury items	numeric: 0-5	The number of luxury items: gym, pool, hot tub, fireplace, doorman.
Additional items	numeric: 0-10	The number of additional items: parking, breakfast, TV, cable TV, iron, dryer, hair dryer, washer, shampoo, essentials.
Safety items	numeric: 0-5	The number of safety items: smoke detector, carbon monoxide detector, first aid kit, fire extinguisher.
Rules	numeric: 0 - 4	The number of rules imposed by the host: no smoking, no parties, no infants, no children.
Location characteristics		

Sqm price	€	How much buying one square meter costs in the listing's street.
Walkability score	numeric: 0-100	A score from walkscore.com on a scale from 0 to 100: how well one can walk from the listing's location to restaurants, bars, supermarkets, etc.
Host characteristics		
Cancellation strictness	numeric	The level of cancellation strictness measured on a scale from 1 (modern) to 5 (very strict)
Reviews	numeric	The number of reviews the listing has received in the past.
Membership months	numeric	The number of months the host is already a member of Airbnb.
Response rate	%	The percentage of how many messages the host answers.
Verified	binary	"1" if host was verified by Airbnb, "0" if not.[6]
Pictures	numeric	The number of pictures the host uploaded for the listing.
Description length	numeric	The length of the listings' description text in number of characters with spaces.

Table 9: Overview of the control variables. The control variables are the same for all three Regressions (A, B, and C).

7.4 Summary statistics

Table 10 shows the summary statistics for all dependent, independent and control variables. The summary statistics refer to the dataset used for Regression A with 27,141 observations. It is interesting to point out that *price* does not seem to vary a lot: with a mean of 4.2[7], the standard deviation is only 0.6 and the range is from 2.3 to 8.3. Moreover, *%female guests*, which has a mean of 0.47 and a standard deviation of 0.24, seems to vary more than *%muslim guests*, which has a mean of 0.69 and a standard deviation of 0.15.

When looking at the mean of *female*, we can see that half of the Airbnb hosts are female (50%) and half are male, reflecting well the actual population of Germany[8]. Moreover, in our sample 4% of Airbnb hosts are Muslim, which is in line with the share of Muslims in the German population, which is around 5.5% according to an estimation from the German Federal Office for Migration and Refugees from 2015 (Röther, 2018). Therefore, we do not have any imbalances between the Airbnb dataset and the actual German population concerning the independent variables.

[6] Hosts can upload a photo of themselves in which they hold their ID. The photo is then checked by Airbnb. If confirmed, a 'verified' badge is displayed on the host's profile.

[7] As mentioned in Section 7.3.1, the variable *price* refers to the natural logarithm of the average price of a listing.

[8] https://www.cia.gov/library/publications/the-world-factbook/fields/2018.html

Variable	Mean	SD	Range	25%	75%
Dependent variables					
Price	4.23	0.60	2.30 – 8.26	3.81	4.60
%muslim guests	0.69	0.15	0.00 – 1.00	0.01	0.08
%female guests	0.47	0.24	0.00 – 1.00	0.33	0.60
Independent variables					
Female	0.50	0.50	0.00 – 1.00	0.00	1.00
Muslim	0.04	0.20	0.00 – 1.00	0.00	0.00
Control variables					
Cleaning Fee	22.91	28.02	0.00 – 634.00	0.00	37.00
Weekly discount	8.08	7.71	0.00 – 62.00	0.00	13.00
Monthly discount	15.65	16.71	0.00 – 86.00	0.00	30.00
Custom pricing	15.78	29.02	0.00 – 100.00	0.00	17.00
Demand pricing	34.19	45.84	0.00 – 100.00	0.00	100.00
Default pricing	47.37	44.53	0.00 – 100.00	0.00	100.00
Guests	2.89	1.85	1.00 – 16.00	2.00	4.00
Bedrooms	1.36	0.73	1.00 – 15.00	1.00	1.00
Bathrooms	1.11	0.32	0.00 – 8.00	1.00	1.00
Luxury items	0.07	0.28	0.00 – 4.00	0.00	0.00
Additional items	4.99	2.03	0.00 – 10.00	4.00	6.00
Safety items	1.22	1.17	0.00 – 4.00	0.00	2.00
Rules	2.03	1.09	0.00 – 3.00	2.00	3.00
Sqm price	3798.00	1779.00	600.00 – 11250.00	2400.00	4800.00
Walkability score	84.42	17.95	0.00 – 100.00	78.00	97.00
Cancellation	2.07	0.86	1.00 – 5.00	1.00	3.00
Reviews	23.62	36.69	0.00 – 453.00	3.00	28.00
Membership	35.55	20.67	0.00 – 114.00	19.00	49.00
Response rate	92.02	19.68	0.00 – 100.00	100.00	100.00
Verified	0.54	0.50	0.00 – 1.00	0.00	1.00
Pictures	12.67	9.14	1.00 – 200.00	7.00	16.00
Description length	1245.00	1083.00	0.00 – 22582.00	491.00	1676.00

Table 10: Summary statistics. ‘SD’ stands for standard deviation and ‘25%’ and ‘75%’ for the 25% and 75% percentile.

8. Empirical results

In this chapter we present the results of the regressions and consequently reject or accept our hypotheses. Chapter 8.1 presents the results for hypotheses 1.1 and 1.2 (price gap) and Chapter 8.2 for hypotheses 2.1 and 2.2 (in- and out-groups). Chapter 8.3 discusses the robustness of our results.

8.1 Empirical results for testing price gaps

Regression A tested Hypotheses 1.1 and 1.2, whether Airbnb hosts in Germany get discriminated by price based on their ethnicity or gender. Table 11 shows the results of the OLS regression with *price* as the dependent variable. The coefficients are given as percentage of the mean of *price*. We conducted a set of linear regressions (1-5) in which we subsequently added more control variables in order to test for robustness. When mentioning ‘Regression A’, we refer to the final regression (5).

<u>Analysis of *muslim* and *female*</u>

When investigating *muslim* we can see that in all five regression sets *muslim* is statistically significant as its p-Value is less than the 5% threshold. The (unstandardized) coefficient stabilizes in the last three regressions and swings between 1.06 and 1.24 with 1.17 being the coefficient of the final model. Therefore, if a host is Muslim, then this is associated with a 1.17% higher price compared to Non-Muslim hosts. It is also worth pointing out that the coefficient has a positive sign, meaning that Muslims charge a higher price on average. Because *muslim* is statistically significant with a p-Value less than 5%, we accept Hypothesis 1.1 that Airbnb hosts in Germany get discriminated by price based on their ethnicity.

Female is also statistically significant with p-Values less than 5% in all regression models. The (unstandardized) coefficient stabilizes for the last three models with a value of -0.58 in the final model. Therefore, if a host is female, then this is associated with a 0.58% lower price compared to male hosts. Since the coefficient has a negative sign, females charge less than males on average. Because *female* is statistically significant with a p-Value less than 5%, we reject Hypothesis 1.2 that Airbnb hosts in Germany do not get discriminated by price based on their gender.

In conclusion, both independent variables, *muslim* and *female*, are statistically significant and, therefore, we accept Hypothesis 1.1 and reject Hypothesis 1.2.

<u>Additional analysis</u>

Moreover, the adjusted R^2 increases with every set of new control variables, meaning that the control variables fit well in explaining the variance of *price*. The R^2 of the final model is 54.57%, meaning that our model can explain 54.57% of the variance of *price*, which can be considered a substantial fraction as *price* varies a lot due to the heterogeneous supply of listings. In fact, our R^2 value is well in line with that of other researchers, ranging from 46.3% (Teubner et al., 2017) to 67.87% (Wang et al., 2015).
The residual standard error of model (5) is 0.41, which is the average amount the predicted value of *price* deviates from the true regression line. When comparing the residual standard error with the mean of *price* (4.23), we see that on average the predictions of our model are off by 9.7%, a considerable low error range.

Regarding the control variables, it is also interesting to point out that the majority of the control variables are statistically significant with very low p-Values. Therefore, most of the variables that are part of our regression model seem to indeed influence *price* and, as additionally indicated by the increasing adj. R^2, are good fits to isolate the independent variables *muslim* and *female*.

Variable	(1)	(2)	(3)	(4)	(5)
Muslim	0.93*	1.57***	1.06**	1.24***	1.17***
	(0.44)	(0.39)	(0.33)	(0.30)	(0.30)
Female	-1.49**	-1.38***	-0.53***	-0.51***	-0.58***
	(0.17)	(0.15)	(0.13)	(0.12)	(0.12)
Price variables					
Cleaning fee		0.22***	0.08***	0.06***	0.04***
		(<0.01)	(<0.01)	(<0.01)	(<0.01)
Weekly discount		0.11***	0.05***	0.02*	0.03**
		(<0.01)	(0.01)	(<0.01)	(<0.01)
Monthly discount		<-0.01***	-0.03***	<-0.01	<-0.01*
		(<0.01)	(<0.01)	(<0.01)	(<0.01)
Custom pricing		0.08***	0.04***	0.05***	0.05***
		(<0.01)	(<0.01)	(<0.01)	(<0.01)
Demand pricing		<-0.01	0.02**	<0.01	<0.01
		(<0.01)	(<0.01)	(<0.01)	(<0.01)
Default pricing		0.05***	0.02**	0.05***	0.04***
		(<0.01)	(<0.01)	(<0.01)	(<0.01)
Listing characteristics					
Guests			1.22***	1.38***	1.39***
			(0.05)	(0.05)	(0.05)
Bedrooms			3.03***	3.33***	3.09***
			(0.14)	(0.13)	(0.13)
Bathrooms			1.16***	0.99***	0.78***
			(0.21)	(0.20)	(0.20)
Private room			-10.21***	-10.52***	-10.24***
			(0.15)	(0.14)	(0.14)
Shared room			-15.12***	-15.53***	-15.30***
			(0.57)	(0.53)	(0.52)
Luxury items			1.93***	2.40***	2.18***
			(0.23)	(0.22)	(0.21)
Additional items			0.68***	0.67***	0.60***
			(0.04)	(0.03)	(0.03)
Safety items			0.08	0.30***	0.34***
			(0.06)	(0.06)	(0.06)
Rules			-0.39***	-0.52***	-0.55***
			(0.07)	(0.06)	(0.06)
Location characteristics					
Sqm price				<0.01***	<0.01***
				(<0.01)	(<0.01)
Walkability				0.05***	0.06***
				(<0.01)	(<0.01)
Host characteristics					
Cancellation strictness					0.49***
					(0.08)
Reviews					-0.04***
					(<0.01)

Membership					0.03***
					(<0.01)
Response					<0.01**
					(<0.01)
Verified					-0.38**
					(0.12)
Pictures					0.12***
					(<0.01)
Description length					<0.01***
					(<0.01)
R^2 adj.	0.003	0.218	0.464	0.533	0.545

Table 11: Results of the OLS regressions. The number of observations is 27,141 (N = 27,141). In the final model, the R^2 is 54.57% and the residual standard error is 0.408.

In order to test for robustness, we conducted a set of linear regressions (1-5) in which we subsequently added more control variables. If the coefficients of the variables under investigation, *muslim* and *female*, would have changed significantly by adding more variables, then the regression would have not been very robust. However, as seen in Table 11, the coefficients changed only slightly. The coefficient of *muslim* swinged around 1.0 and only had one outlier in model (2) with a coefficient of 1.57. The coefficient of *female* had a little break from around 1.38 in model (2) to 0.53 in model (3), but then stabilized in the last three models at around 0.50.

8.2 Empirical results for testing in- and out-groups

Hypothesis 2.1 expected that there are in- and out-groups among Airbnb users formed based on ethnicity (Muslim, Non-Muslim). To test that hypothesis, we ran an OLS regression with *%muslim guests* as the dependent variable and *muslim* as the independent variable after controlling for several other variables (Regression B). As seen in Table 12, *muslim* is not statistically significant as the p-Value is higher than the 5% threshold. Put in other words, it is very likely that whether the host is Muslim or not does not influence the percentage of how many Muslim guests he/she has. Therefore, we did not find existence for in or out groups when looking at Muslims and Non-Muslims. To sum it up, because *muslim* is statistically insignificant with a p-Value higher than 5% we reject Hypothesis 2.1.

Hypothesis 2.2 expected that there are no in- and out-groups among Airbnb users based on gender (male, female). To test that hypothesis, we ran Regression C. Table 13 shows the results of the Regression C with *%female* guests as the dependent variable and *female* as the independent variable after controlling for other variables. The p-Value for *female* is not statistically significant. Therefore, it is very likely that whether a host is female or not does not influence the percentage of female guests the host has. Consequently, we did not find existence of in or out groups based on gender. To sum it up, because *female* is statistically insignificant with a p-Value higher than 5% we accept Hypothesis 2.2.

In conclusion, we did not find in- or out-groups concerning *muslim* and *female* and, therefore, we reject Hypothesis 2.1 and accept Hypothesis 2.2.

	Coefficient	Standard error	p-Value
muslim	-0.11	0.06	0.10
R^2	0.1136		
N	500		

Table 12: Results of the OLS regressions with *%muslim guests* as the dependent variable. The independent variable is *muslim*. The control variables are the same as in Regression A (see Table 11).

	Coefficient	Standard error	p-Value
female	-0.02	0.02	0.24
R^2	0.0792		
N	500		

Table 13: Results of the OLS regressions with *%female guests* as the dependent variable. The independent variable is *female*. The control variables are the same as in Regression A (see Table 11).

8.3 Robustness

As mentioned in Chapter 7.1, since we ran an OLS regression, one assumption is that the population, from which the residuals are drawn, has a constant variance, which is also called homoscedasticity. Therefore, we tested for the contrary, heteroscedasticity, by checking whether the residuals are unequally scattered. More specifically, we tested whether the residuals spread systematically over the range of measured values. For that purpose, we analysed the residuals vs. fitted plot (see Figure 16). As seen in the plot, there is no significant systematic change of the residuals as they are all equally spread around the zero line.

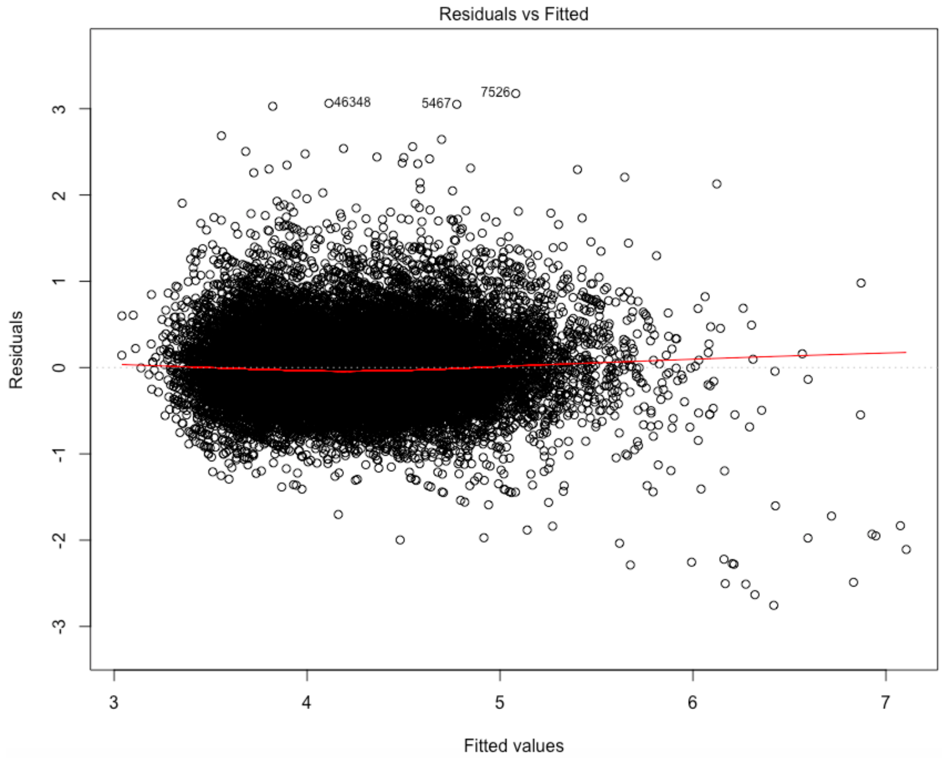

Figure 16: Residuals vs. fitted plot for the final regression model (see Table 11).

9. Discussion

In Chapter 9.1 we first discuss our empirical results of the price gaps analysis. As mentioned in Chapter 5.2, the last step of a deductive research approach is the discussion of the theory (Bryman & Bell, 2003). Therefore, Chapter 9.2 discusses our empirical results of the in- and out groups analysis as well as the applicability of social identity theory in the context of discrimination on Airbnb. Finally, this chapter rounds up with a discussion about validity, reliability and replicability of our study (9.3).

9.1 Discussion of price gaps analysis

While the results of the price gaps regression are statistically significant with p-Values below the 5% threshold, the coefficients of *muslim* (1.17%) and *female* (0.58%) are rather small. Therefore, we have to question whether the magnitude of our results, that is the coefficients of *muslim* and *female*, are large enough in order to declare them as practically relevant. In order to do so, we (i) refer to past studies that also investigated host discrimination on Airbnb and (ii) put the results in relation to the absolute average price per night on Airbnb. We do so for both ethnicity and gender.

Looking at previous studies that investigated ethnicity-based discrimination, as presented in Table 14, Wang et. al (2015) found a 20% price gap against Asian hosts, Edelman and Luca (2014) a price gap of 12% against Blacks, Kakar et al. (2017) a price gap of 8-10% against Hispanics and Asians, Cansoy and Schor (2016) a price gap of 12% against Blacks and Laouénan and Rathelot (2017) a price gap of 3.2% against minorities. Clearly, the price gaps prior research has found are much larger than ours. But what is more, while all previous studies revealed discrimination against minorities, our study actually showed the contrary: according to our results the minority, Muslims, charge 1.17% more than Non-Muslims. Putting the relative difference into the Airbnb context, the average price per night in Germany is $85. This means that Muslims receive $1.45 more per night than Non-Muslims, which we interpret as a rather low amount. To conclude, the magnitude of our results is much lower than the one of previous research and the absolute price difference ($1.45) is also quite low. Thus, although we accepted Hypothesis 1.1 that ethnicity-based discrimination exists in Germany, we conclude that the magnitude of the discrimination is practically not very large.

Authors	Location	Group	Price gap
Ethnicity-based discrimination			
Wang et al. (2015)	US	Asians	20%
Edelman & Luca (2014)	US	Blacks	12%
Kakar et al. (2017)	US	Hispanics, Asians	8-10%
Cansoy & Schor (2016)	US	Blacks	12%
Laouénan & Rathelot (2017)	US, Canada & Europe	Blacks, Muslims	3.2%
Our thesis	Germany	Muslims	1.7%
Gender-based discrimination			
Kakar et al. (2017)	US	Females	n.s.
Edelman et al. (2017)	US	Females	n.s.
Our thesis	Germany	Females	0.58%

Table 14: Overview of the price gaps found in past studies compared with the price gaps in our study for both ethnicity- and gender-based discrimination.

Looking at previous studies that investigated gender-based discrimination, Kakar et al. (2017) and Edelman et al. (2017) both did not find statistically significant results. In contrast, we found statistically significant results, but the magnitude of our results (0.58%) seems very low. Putting that relative difference into relation to the average price per night of $85, females receive $0.49 less per night than males, which is a small amount. To conclude, we rejected Hypothesis 1.2 that gender-based discrimination does not exists in Germany. However, the magnitude of the discrimination that we found, is practically not very large.

When comparing our findings with previous studies, we found that our results differ significantly, mainly in two points: (1) in our study the majority (Non-Muslims) gets discriminated and not the minority (Muslims) and (2) the magnitude of our results is very low. In a further step, it is important to analyse why our results differ so much from those of past research. Looking at Table 14, we identified three possible reasons.
First, it is important to remember who the trigger for the discrimination against hosts is: the guests. The question that then arises is whether the guests in Germany differ from the guests in the US (where most of the past research was conducted). It sounds reasonable that this would be the case. For instance, in Germany there might be more European guests due to the geographic proximity. Hence, if the guests in Germany and the US differ significantly, then their discrimination behaviour might also differ, which could explain the differences between our results and the results of past research.
Second, the minority under investigation in our study (Muslims) is different from the ones of past research (mainly Blacks and Asians). Therefore, it could be that Muslims in Germany get less discriminated than Blacks or Asians in the US. This would also mean that Airbnb guests in Germany might not discriminate Muslims that much, but other ethnic groups.
Third, we used different control variables than previous researchers. Especially within location characteristics we considered very granular variables as we collected the price per sqm and the walkability score for the longitude and latitude coordinates of every listing. Other researcher did not consider the location characteristics on such a detailed level. For instance, Kakar et al. (2017) considered location variables only on a neighbourhood level and Cansoy and Schor (2016) only on a census tract level. Therefore, the more precise consideration of differences in locations in our study could be a reason for the different results. For instance, if a specific ethnic group is systematically living in locations with cheaper rental prices, and if we better capture this effect through our more granular variables, then this could explain the different results. Besides the more granular location characteristics, we also integrated the three different pricing mechanisms (default-, custom-, and demand-based pricing), which previous researcher have not done yet.

Why the majority (Non-Muslims) and not as in other studies the minority was discriminated is difficult to say. We do not want to make vague speculations and leave that question open for further research, which is further discussed in Chapter 10.3.

9.2 Discussion of in- and out-group analysis and social identity theory

This subchapter discusses social identity theory as the fifth step of the deduction process by Bryman and Bell (2003). Chapter 9.2.1 discusses the applicability of the theory in the context of discrimination on Airbnb and Chapter 9.2.2 outlines advantages and disadvantages of social identity theory.

9.2.1 Applicability

According to social identity theory, discrimination is explained by the formation of in- and out-groups. In our study we found that (i) no in- and out-groups exist based on gender and ethnicity and that (ii) there are only small price gaps due to ethnicity- and gender-based discrimination. Comparing our study with other studies, there is only one further study that conducted an analysis of in- and out-groups: Laouénan and Rathelot (2017) did a so-called segregation analysis. Interestingly, their results are similar: they also found no existence of in- and out-groups and a small price gap of only 3.2%, which even decreased to 0.7% when the researchers controlled for the number of reviews.

When putting the results of our regressions in relation with what social identity theory predicts, there is a contradiction. As we did not find in- and out-groups based on ethnicity and gender, according to the theory, there also should not be price gaps based on ethnicity and gender. However, we found price gaps of 1.17% and 0.58% for Muslims and females, respectively.
However, the magnitude of our results must be considered. As discussed in Chapter 9.2, compared to previous papers and compared to the absolute average price per night on Airbnb, the practical magnitude of our results is rather low. In other words, the price gaps could be so low that they were not caused by in- and out-groups. Thus, social identity theory could still be applicable.

Thus, when considering our empirical results from a practical point of view, the predictions of social identity theory hold in our study. In our eyes, our results are the first level of proof for assessing the applicability of social identity theory in the context of discrimination on Airbnb as can be seen in Figure 17. Our study builds the base of the pyramid as we proved the no-existence of in- and out-groups simultaneously with the no-existence of large price gaps.

Further research will have to test whether the upper levels of the pyramid exist. The second level describes the co-existence of in- and out-groups and significant price gaps. As at this level no causal relation between the two can be inferred, the third level describes that the existence of in- and out-groups leads to price gaps, which proves the applicability of social identity theory for the context of discrimination on Airbnb. The second stage does not automatically lead to the third stage as there could be an unknown factor X that causes both price gaps and in- and out-groups. In that case, in- and out-groups would not really lead to a price gaps, but rather coexist by accident because of that factor X.

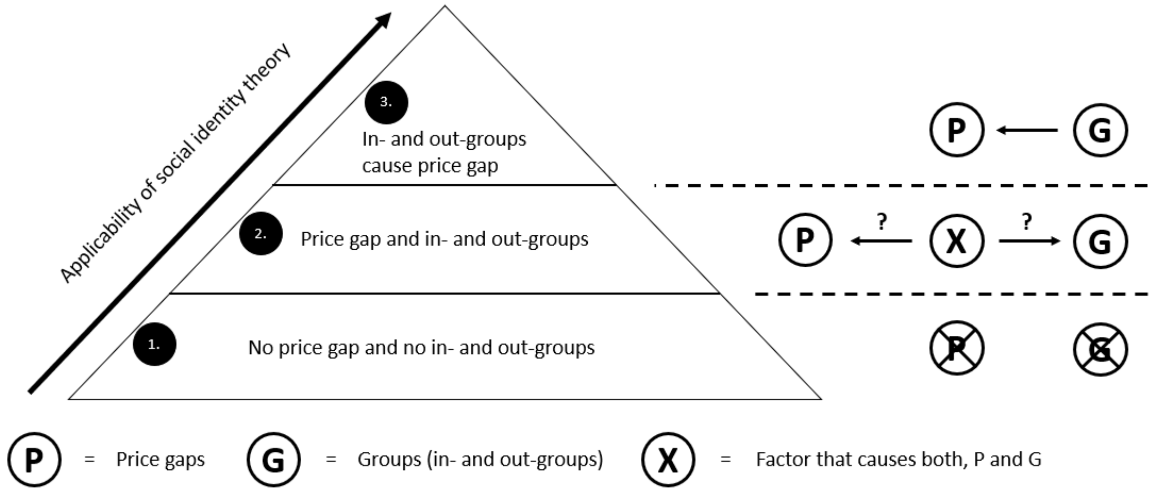

Figure 17: Level of applicability of social identity theory based on three levels of empirical findings.

9.2.2 Advantages and disadvantages

A clear advantage of social identity theory is that, if enough data is given, the existence of in- and out-groups can be easily proven by applying regression models that isolate the effects of the characteristics under investigation. Another advantage is the flexibility in terms of the characteristics under investigation. This theory can be used in many different discrimination research areas ranging from ethnicity to same sex to obesity discrimination. A third advantage is that the theory has been proved by several experiments. For instance, Tajfel (1970) with his intergroup discrimination experiment, Cialdini (1984) with the football game observation and Zimbardo, Haney, Banks and Jaffe (1972) with the Stanford prison experiment proved in-group favouritism and discrimination against the out-group based on social identity theory.

A first disadvantage is that, theoretically, there are infinite possibilities in which ways in- and out-groups can be formed: by ethnicity, gender, attractiveness, etc. Therefore, when testing social identity theory researchers might have to try out several different characteristics until the existence of in- and out-groups is found. A second disadvantage is that the theory is descriptive and not prescriptive. Thus, it might explain why discrimination exists, but it does not give advice how the issue can be solved.

9.3 Validity, reliability, and replicability

In this subchapter we discuss the validity of our results based on four forms of validity defined by Bryman and Bell (2003). Moreover, our study's reliability and replicability are discussed.

<u>Internal validity</u>

Internal validity is about how confident one can be that the independent variables under investigation, and no other variables, are causing a change in the dependent variable (Bryman & Bell, 2003). With respect to our research, the question is: are really ethnicity and gender the causes for the observed changes in price or are there other factors? In order to isolate the effects of ethnicity and gender, we used a large number of control variables, ranging from the listing's rating to the number of pictures uploaded (see Chapter 7.3.3). As mentioned in Chapter 8.1.1, most control variables are statistically significant and the R^2 is as high as the ones from previous research (see Chapter 8.1.1). Therefore, we conclude that the internal validity is fairly high.

<u>External validity</u>

External validity concerns about to which extent one can generalize the findings of the study beyond the specific context (Bryman & Bell, 2003). In our case we analysed discrimination on Airbnb in the 82 largest German cities. Therefore, the question is whether we can generalise our results on (i) whole Germany and (ii) all countries.

When analysing the generality on whole Germany, we can assume that with the investigation of the 82 largest German cities, our study covered a large part of the German Airbnb market. We also want to highlight the range of the cities, which goes from large metropolitan cities such as Berlin and Munich to small cities with just 100,000 inhabitants. Therefore, we conclude high external validity for whole Germany.

When analysing the generality on all countries, one has to consider two important facts. Firstly, Germany differs from other countries in terms of the minority distribution. Muslims are the largest minority, making up around 5.5% of the whole population (Röther, 2018). However, other countries have different minorities. For example, Blacks make up 12.6% of the US population (Humes, Jones & Ramirez, 2011). Therefore, it is difficult to generalize findings about racial discrimination from one country to other countries. Secondly, there are reasons to believe that the actual actors who cause the discrimination, in our case the Airbnb guests, differ among the countries under investigation. It seems reasonable to assume that more European Airbnb guests make vacations in Germany than in the USA because of the geographical distance. Then, the Airbnb guests in Germany and USA would differ from each other. This would suggest that the results of the study could also be different. In fact, as seen in Chapter 9.1, our results differ significantly from the results of previous research in the US. Therefore, we conclude that the external validity on all countries is low.

<u>Construct validity</u>

Construct validity answers the question of whether or not the measures used in a study really measure the concept under investigation (Bryman & Bell, 2003). In our case the measure is price and the concept under investigation is discrimination. We decided to take price as the measure since the price plays an important key role on Airbnb. As Ikkala and Lampinen (2015) found in their study, financial gains provide an important factor driving host's participation. Moreover, according to Liang (2015) guests choose Airbnb to meet people and to save money. Especially the price is a competitive advantage towards hotels as overall costs for hosting are low (Oskam & Boswijk, 2016). Therefore, based on its central role, we assume that if discrimination exists on Airbnb, then discrimination would be reflected in price. In fact, as seen in Table 4 from Chapter 6.1, almost all previous researchers have used price in order to measure discrimination on Airbnb.

<u>Ecological validity</u>

The question of ecological validity is whether the findings are applicable to the natural surrounding of the people (Bryman & Bell, 2003). Put in other words, the more the researcher intervenes in the natural surrounding, for example by conducting a laboratory experiment, the more likely the findings do not apply in the actual natural surrounding. We did not intervene in the natural setting of the actors, in our case the Airbnb guest and hosts, as we just collected the data with the web crawler after the actors had made their decisions. Therefore, ecological validity is high.

Reliability

Reliability is concerned with the question whether the data values are repeatable within another data collection process (Bryman & Bell, 2003). The Airbnb website changes continuously due to its nature. New listings are published, and inactive ones taken from the platform. Moreover, hosts can constantly adjust their description of listings, upload new pictures, change the prices and much more. Hence, the more time passes, the more differences there will be between our dataset and the new data collected. Therefore, reliability is low due to the nature of Airbnb.

Replicability

Replicability concerns whether the data collection process can be replicated by other researchers (Bryman & Bell, 2003). Although in future data collection processes the data points will not have the same values due to issues with reliability, researchers can replicate our data collection process. Therefore, we explained the data collection process in great detail and we are willing to share the source code of our web crawler on request.

10. Contributions, limitations and future research

This chapter outlines the contributions of our study (10.1), limitations (10.2) as well as avenues for future research (10.3).

10.1 Contributions

With our purpose in mind, we contributed to the current body of discrimination research in three ways. First, we filled the research gap of investigating more countries outside the US by looking at Germany. It is important to widen the scope of research beyond the US as the US is only one of many countries in which Airbnb is present. Moreover, in terms of culture and ethnicities the US is quite a unique country with a high degree of immigration. Further studies would reveal whether previous findings of discrimination are only an US specific issue or a general issue of Airbnb. Interestingly, for Germany we found very different results compared to previous US studies.
Second, we introduced an underlying theory which most previous studies are lacking. Such a theory is important to not only measure discrimination on Airbnb, but also to better understand the underlying reasons why subjects discriminate. In our view, a fundamental theory could provide insights in answering such questions as well as help as guidance for counteracting legal measures. As discussed in Chapter 9.1, our study builds the base for testing the applicability of social identity theory in the Airbnb discrimination context: proving the simultaneous non-existence of both large price gaps and in- and out-groups.
Third, we added control variables that previous researchers have not considered yet. This is important in order to better isolate the effects of ethnicity and gender, since this can have a significant impact on the results. For example, to the best of our knowledge, previous researchers did not use as granular location-based control variables as we did. By combining the Google Maps API with additional web crawling of homeday.de and walkscore.com, we were able to determine the average square meter price (*sqm price*) and location attractiveness (*walkability*) of each of the 27,141 Airbnb listing by using the listing's latitudinal and longitudinal coordinates. In fact, as seen in Table 11, it turned out that both variables are statistically significant with p-Values less than 0.1%, proving that both most likely influence the price. We outlined the crawling process in great detail in Chapter 6.3 so that future researcher can implement these control variables in their studies. Moreover, to the best of our knowledge we were also the first ones to add the three different pricing mechanisms out of which Airbnb hosts can choose: default-, custom-, and demand-based pricing[9]. Clearly, when running a regression with price as the dependent variable, it is important to control for the different price mechanisms. In fact, as seen in Table 11, default- and custom-based pricing are statistically significant.

10.2 Limitations

Our research is exposed to mainly three limitations. First, we assumed that prices by hosts are demand-driven. However, there can be other reasons: Ikkala and Lampinen (2015) showed that some hosts lower their prices to have more options to choose their guests and others were convinced that

[9] We guess that previous researcher did not consider these variables since they cannot be found in the source code of Airbnb's website (which normal web crawler use for collecting the data). Instead, this information must be deviated by using Airbnb's API. However, for the Airbnb API no public documentation exists and, therefore, it is more difficult to collect the information.

lower prices lead to a more enjoyable hosting experience. For example, if female hosts would systematically set lower prices than male hosts in order to be able to choose from a wider pool of guests, then the price gap of 0.58% would not be the result of discrimination against females, but rather a different hosting strategy employed by females.
Second, despite of being as thorough as possible, we cannot assure that we collected all listings in the geographic areas we considered. Therefore, if the crawler would have missed to collect certain listings in a systematic way, then our results would be biased. In fact, as explained in Chapter 6.4, we filtered the initial dataset, reducing the number of listings being analysed from 76,061 to 27,141[10]. However, similar to Cansoy and Schor (2017) we are convinced that web crawlers are the best way to obtain data as Airbnb is reluctant to share data with researchers.
Third, our study is cross-sectional as we have collected the data only at one point in time. Therefore, we are not able to consider changes in time, for example churn of guests and hosts. Consequently, we are also not able to see systematic changes over time, especially whether a certain type of hosts left Airbnb. In general, we are not able to make conclusions about causality.

10.3 Future research

We mainly see five avenues for future research. First, future research should challenge the applicability of social identity theory for investigating discrimination on Airbnb. Looking at Figure 17, in a first step the theory should be applied in a market setting in which large price gaps have already been identified in order to test whether price gaps and in- and out-groups coexist. This could be done, for example, in certain geographical areas in the US where price gaps have already been found. In a next step, future research should investigate the third level of the pyramid, the causal relationship between the two phenomena, in particular whether in- and out-groups cause the price gaps. This could be realized by conducting a longitudinal study.
Secondly, further studies outside the US should be conducted in order to find out whether discrimination found in past research is an US specific issue or a general issue on Airbnb. Therefore, we call to conduct more studies in Europe in order to compare their results with ours. In a next step, research should investigate more geographic areas, such as Latin-America and Asia.
Thirdly, future research should investigate the underlying reasons why we found discrimination against the majority (Non-Muslims) and not against the minority (Muslims), which is in contrast to past studies. Researcher investigating this phenomena would probably have to shift to a rather qualitative approach. A possible way to conduct such a study would be to interview Airbnb guests who decided to stay with Muslims and Airbnb guests who decided to stay with Non-Muslims.
Fourthly, future research should include more variables that explain the variance in price. One way of doing so could be to consider the variables we have integrated in our study: location-based attractiveness through walkability and price per sqm. What is more, as already outlined above, researchers could also measure whether hosts set lower prices in order to choose from a wider pool of guests. Another factor for which researchers should control is the fact that some hosts might run a low-pricing strategy: they might set lower prices in order to increase the amount of bookings and, hence, their return. While walkability and price per sqm can be collected by a web crawler, the latter

[10] The filter process could of course have an effect on our end results. For instance, if the listings that did not have a walkability score, and hence were filtered out, would have something systematically in common (for instance, most of those listings are hold by Muslims), then our results would be biased.

kind of data cannot be collected by a web crawler. Researchers would have to use other tools, such as interviews.

Fifthly, future research should try to collect a more reliable, granular and larger dataset, which unfortunately seems only possible in cooperation with Airbnb. If Airbnb would provide a dataset, then the uncertainty of whether web crawlers collected the data in wrong ways would be eliminated and the dataset could be considered as more reliable (Gelman, 2016). Moreover, Airbnb could easily provide larger datasets of several whole countries, which is almost impossible to collect with web crawlers. Finally, Airbnb possesses extremely granular data about both hosts and guests, ranging from their full name to their age. These additional data points could be used as control variables in future regression to even further isolate the effects of gender and ethnicity.

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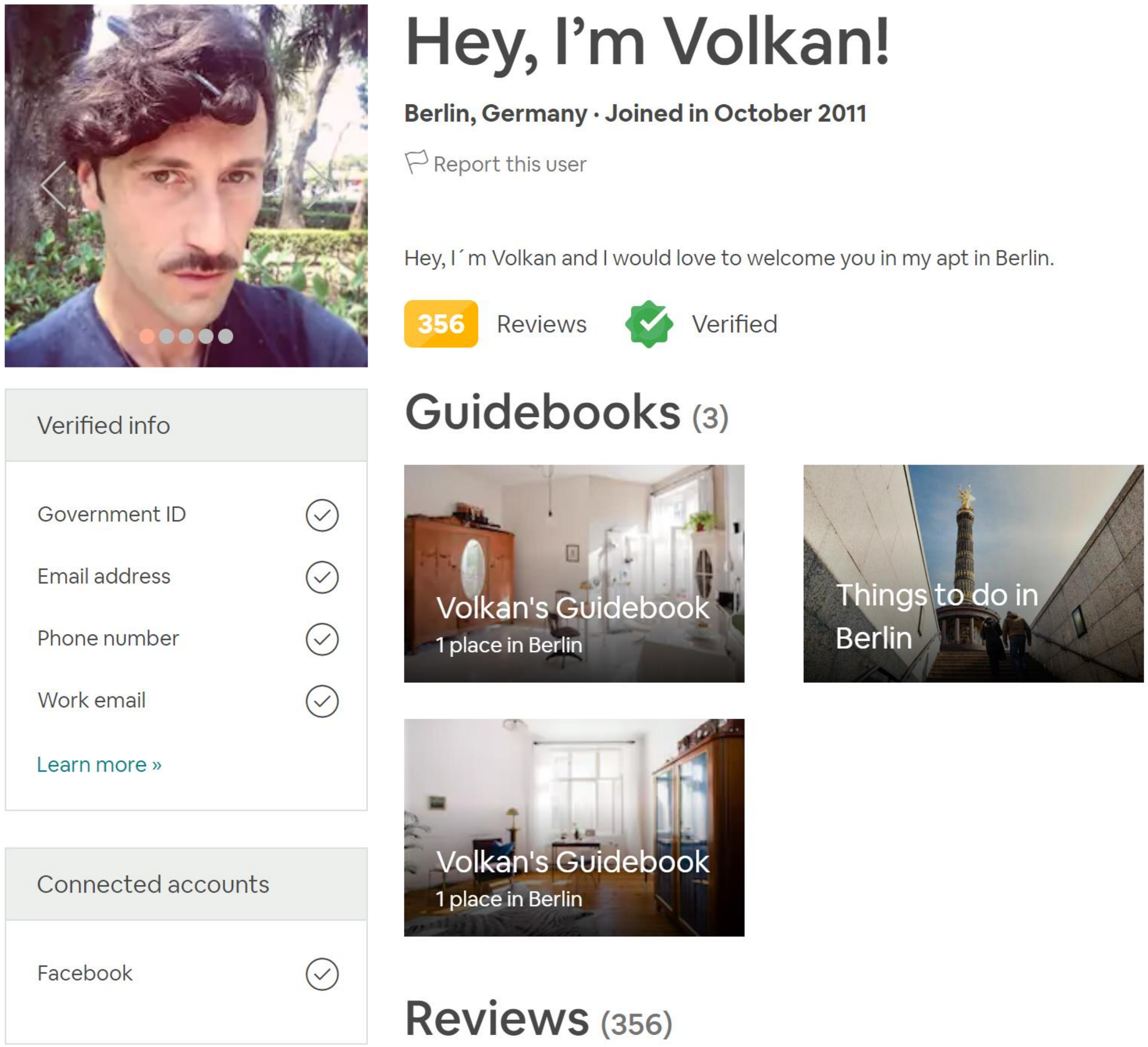
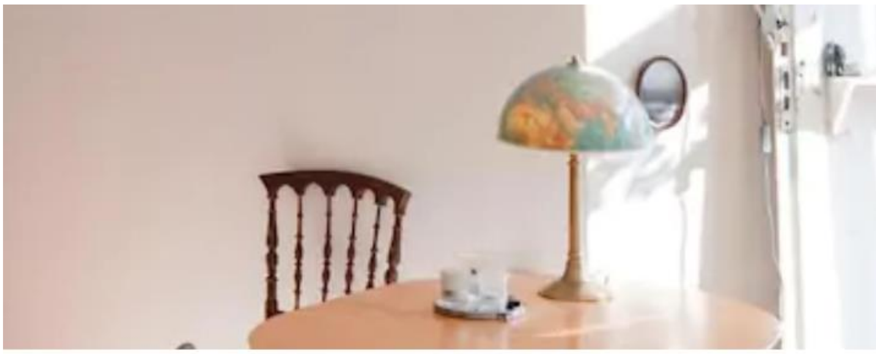
12. Appendix

Appendix A: A profile of a host on Airbnb (from 24.03.2018).



Appendix B: Screenshot of an Airbnb listing (from 24.03.2018).



ENTIRE APARTMENT

Welcome to Apartment "Kleinod"!

Berlin

Volkan

2 guests 1 bedroom 1 bed 1 bath

The space

Describing words for the apartment:
Cottage, shabby-chic, rustic, scandinavian...arranged with love.
You get the entire apartment.
The apartment is in the upcoming and interesting district Neukölln and very quite because it's in the backyard!
Post office and pharmacy are in the house!
Everything else in the vicinity.

Read more about the space

Contact host

Amenities

Wifi	Hair dryer
Iron	Essentials
Shampoo	Heating

Show all 12 amenities

House Rules

No parties or events
Check-in is anytime after 12PM (noon)
Check out by 11AM

Read all rules

Cancellations

Moderate

Cancel up to 5 days before check in and get a full refund (minus service fees).
Cancel within 5 days of your trip and the first ni...Read more

Get details

225 Reviews ★★★★★

Search reviews

Accuracy	★★★★★	Location	★★★★½
Communication	★★★★★	Check In	★★★★★
Cleanliness	★★★★★	Value	★★★★½

Rebecca
October 2017

The apartment was really beautiful and looked exactly like in the picture. Volkan was very friendly and always responded quickly to every question we had. Truly amazing bed and the place is in a good location.

From
€49 per night
★★★★★ 225

Dates
Check In → Check Out

Guests
1 guest

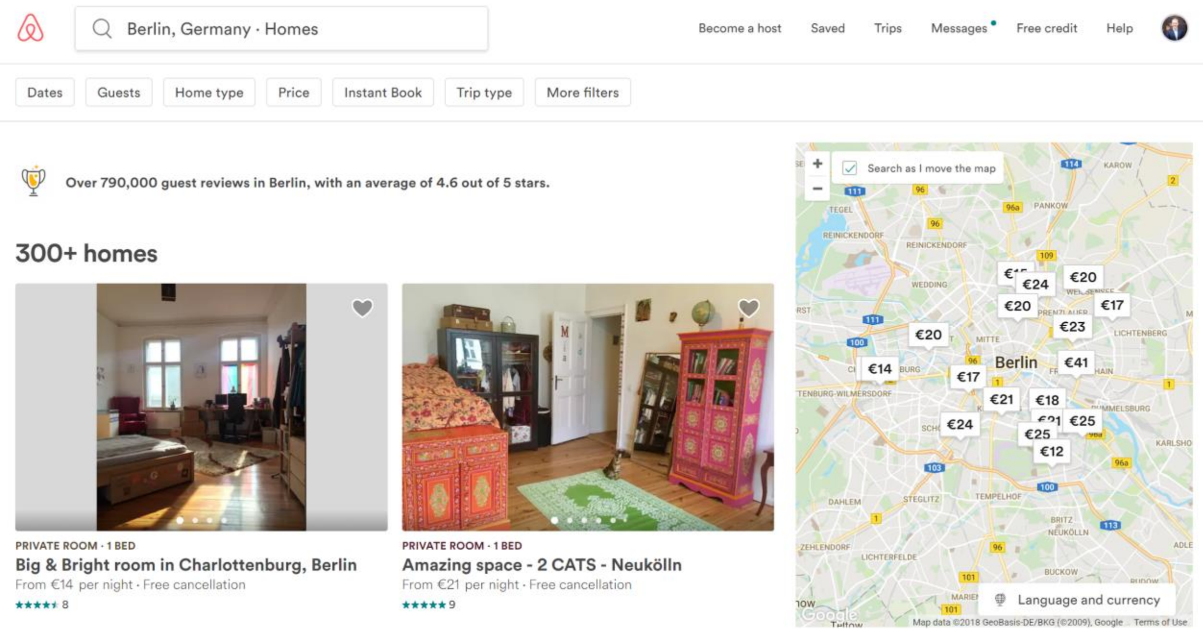
Request to Book

You won't be charged yet

This home is on people's minds.
It's been viewed 500+ times in the past week.

Report this listing

Appendix C: Screenshot of the Airbnb website when searching for listings (from 24.03.2018).



Appendix D: List of all 82 cities we considered in our study.

Cities
Berlin
Hamburg
Munich
Cologne
Stuttgart
Frankfurt am Main
Braunschweig
Krefeld
Halle (Saale)
Kiel
Magdeburg
Oberhausen
Freiburg
Luebeck
Erfurt
Hagen
Rostock
Kassel
Hamm
Mainz
Saarbruecken
Herne
Muelheim
Osnabrueck
Solingen
Ludwigshafen am Rhein
Leverkusen
Oldenburg
Neuss
Potsdam
Heidelberg

Paderborn
Darmstadt
Wuerzburg
Regensburg
Wolfsburg
Recklinghausen
Goettingen
Heilbronn
Ingolstadt
Ulm
Bottrop
Pforzheim
Offenbach
Bremerhaven
Remscheid
Reutlingen
Furth
Moers
Koblenz
Siegen
Bergisch Gladbach
Jena
Gera
Hildesheim
Erlangen
Witten
Salzgitter
Trier
Zwickau
Nuernberg
Dresden
Bochum
Wuppertal
Bielefeld
Bonn
Mannheim
Marienthal
Karlsruhe
Wiesbaden
Muenster
Gelsenkirchen
Aachen
Moenchengladbach
Augsburg
Bremen
Dortmund
Duesseldorf
Duisburg
Essen
Hannover
Leipzig