# The End of the Sharing Economy? Impact of COVID-19 on Airbnb in Germany

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**Abstract**

*This paper analyzes the effect the COVID-19 pandemic is having on the sharing economy. We focus on hosts' behavior in the German shared housing market and examine hosts' adaption to the pandemic state. Using monthly data from January 2019 until December 2020 for the city of Berlin, we conduct a probit model regression analysis and investigate the influence of several Airbnb-listing-specific factors and unemployment on the probability of renting the Airbnb accommodation. Through this big data analysis, we find that hosts switch from short-term to long-term options and rent relatively more entire apartments than shared ones during the COVID-19 pandemic compared to the pre-pandemic state.*

## 1. Introduction

As humankind has been continually confronted with pandemics in history, the spread of the coronavirus disease (COVID-19) is not an entirely new difficulty. For instance, the Spanish Flu caused over 50 million mortalities worldwide and led to rising poverty and unemployment (Taubenberger & Morens, 2006; Karlsson & Nilsson & Pichler, 2014). Diverse studies investigating the impact of diseases and pandemics, on the hospitality industry (Alan & So & Sin, 2006; Chen & Jang & Kim, 2007; Chien & Law, 2003; Kim & Chun & Lee, 2005; Wu & Law & Jiang, 2010). Worldwide, 57 million tourist arrivals have been lost during epidemic outbreaks from 1980 to 2019. The loss of tourism spending reached US$ 95 billion for the same period (Škare, Soriano & Porada-Rochón, 2021).

During the COVID-19 pandemic, travel restrictions, and border closures led to a decrease in domestic and international tourist flows (Gössling et al., 2020). Furthermore, the United Nations World Tourism Organization declared tourism one of the hardest-hit industries during the spread of SARS-CoV-2, concerning both travel demand and travel supply (United Nations World

Tourism Organization, 2020). Therefore, concerns about the future of the tourism and hospitality sector have arisen worldwide.

Numerous studies analyze the vast impact of the COVID-19 pandemic on the tourism industry. Using data from 1995 to 2019 in 185 countries Škare et al. (2021) estimated the impact of COVID-19 on the worldwide tourism sector. The researchers proved that the effects of COVID-19 are more destructive, and the industry's recovery is likely to last longer than the expected average recovery period of ten months. Farmaki et al. (2020b), on the contrary, argue that characteristics of the travel industry will return to pre-pandemic levels once the situation is under authorities' control. Ying et al. (2020) postulate that the effect of the spread of SARS-CoV-2 will be a long-term addition to tourists' risk perception. Jayawardena et al. (2008) argue that risk assessment, planning, and contingency plans will be relevant for the recovery of the entire tourism sector.

Regarding the future of peer-to-peer renting alert have been raised due to the high vulnerability of the sector to pandemic outbreaks. Fidrmuc et al. (2021) show that the home sharing sector was hit hard by the COVID-19 pandemic. Their research describes the overall negative impact but does not specify how the industry might adapt, or has already adapted. A more profound examination of how COVID-19 influences the shared housing sector has been presented by Gossen (2021) and Fidrmuc (2021), which both analyze the effect of COVID-19 on *Airbnb*. Our research is based on these two papers. Therefore, we are asking: Does the COVID-19 pandemic lead *Airbnb* hosts to exit the market, switch from short term to long-term options, and rent rather whole apartments than shared ones?

For our analysis we focus on the shared housing market of Berlin. The monthly data covers the period from January 2019 to December 2020. Our estimation strategy is a probit model.

The remainder of this study is organized as follows: Chapter 2 deals with the existing literature. Chapter 3 describes the data and explains the econometric model. Chapter 4 shows the results. Chapter 5 discusses limitations to our research, summarizes and concludes.

## 2. Literature review

## 2.1. The sharing economy during the COVID-19 pandemic

The sharing economy is an extensively discussed topic in research, and its core idea became a predominant business model in the digital economy (Kraus & Roig-Tierno & Bouncken, 2019; Richter et al., 2017). Cheng (2016) defines the sharing economy as "peer-to-peer sharing of access to underutilized goods and services, which prioritizes utilization and accessibility over ownership". Home sharing, i.e. peer-to-peer accommodation, is based on digital platforms that allow individuals to rent their underutilized properties for a short period (Belk, 2014).

While the sharing economy has enormous potential to meet consumer's demand and create new income sources, it can also disrupt whole industries. For example, Reichle et al. (2021) show that home-sharing has significantly contributed to a rise in rents and house prices in European cities. Regarding COVID-19, Batool et al. (2020) empirically analyze the impact the pandemic had on five sectors of the sharing economy using Google Trend Data from 2019 and 2020. They found that transportation and accommodation experienced a negative influence. In comparison, COVID-19 and its related lockdown positively impacted freelance work, online deliveries, and streaming services.

With the expanding importance of the sharing economy, peer-to-peer accommodation has developed to disrupt the traditional hospitality industry (Sigala, 2017; PwC, 2015). The advantage of peer-to-peer accommodations for guests is the provision of comparatively cheap housing options (Stors and Kagermeier, 2015; Tussyadiah, 2016) that offer a more authentic alternative compared to hotels (Mody & Hanks & Dogru, 2019; Mody & Suess & Lehto, 2019; Paulauskaite & Powell & Coca-Stefaniak & Morrison, 2017). At the same time, hosts can profit from an additional source of income (Farmaki and Kaniadakis, 2020a; Guttentag, 2015) and practice entrepreneurship (Zhang & Bufquin & Lu, 2019). Another vital distinction between hotels and peer-to-peer accommodations is that the latter offers a "home away from home" (Liang & Choi & Joppe, 2018: 43) and social interaction between the local host and the renter (Moon & Miao & Hanks & Line, 2019) as well as social gratification for hosts (Lampinen & Cheshire, 2016). However, the spread of SARS-CoV-2 brought the risk of contagion when either sharing an apartment or socially connecting to the hosts (Batool et al., 2020; Farmaki & Stergiou, 2019). Consequently, threats exist to the sharing economy caused by the ongoing pandemic (Conger & Griffith, 2020).

## 2.2. Impact of COVID-19 on Airbnb and Peer-to-Peer renting

As peer-to-peer accommodation is growing in importance within the hospitality sector, much research has been done in a short time about the impact of COVID-19 on *Airbnb* or peer-to-peer accommodation in general.

*Overall quantitative changes*
Chen & Cheng & Edwards & Xu (2020) measured the financial losses of *Airbnb* hosts in Greater Sydney and found by comparing August 2020 to January 2020 that hosts underwent an income loss of about 89.5% on average.
Shen & Wilkoff (2020) have affirmed that, in general, the number of active listings on *Airbnb* dropped by 25% during the pandemic, and hosts who kept their listings active lost 22% of their income, while occupancy rates declined by 20%. At the same time, properties perceived as clean experienced an income increase of 17.5% and an expansion in occupancy rates by 16.5%. For their analysis the authors used data from Austin, Texas.
Boros & Dudas & Kovalcsik (2020) likewise found evidence for a reduction in occupancy rates during the spread of SARS-CoV-2 using data from 15 cities. Moreover, they examine the effects on underlying motives in detail and find that "the local pandemic situation had the most significant impact on bookings and occupancy rates" (Boros & Dudás & Kovalcsik, 2020: 363). Furthermore, local market characteristics and the pandemic status in travelers' home countries played a significant role in bookings and cancellations.
Jang & Kim & Kim & Sam (2021) studied the change of *Airbnb* performance during the ongoing pandemic in Florida depending on the purpose of the trip and the perceived thread by COVID-19. In two experimental studies they were able to show that *Airbnb* hosts experienced different losses in urban and rural areas and that the perceived threat by COVID-19 is lower for business tourists than for leisure tourists.

Hu and Lee (2020) similarly examined the determinants for global *Airbnb* booking activities. They found that local lockdowns lead to a decrease of 57.8% in booking activities globally. Moreover, they show that a doubling of cases leads to a 4.16% decrease in bookings. The authors could also prove that the sensitivity of bookings decreases with an increasing geographic distance to Wuhan and increases with "government stringency of lockdown policies" and "human mobility" within an area. Diverging from previous studies, their data shows no significant changes in the number

of active listings on the supply side but instead lower prices per night together with dynamic pricing strategies. Focusing on the demand side, they discover a reduction in travel flows influenced by lockdowns and the spreading of SARS-CoV-2 in tourists' home countries or towns.

*Hosts' behavior towards losses rooting in the spread of SARS-CoV-2*
Financial motives showed to be the primary decisive reason for hosting (e.g., Guttentag, 2015), as around a third of the participants admitted in a survey that income from hosting was their first source of income (Farmaki et al., 2020a). COVID-19 led to hosts struggling financially due to a sharp decrease in bookings (Farmaki et al., 2020a; Johnson & Davis, 2020). Being informal employees of *Airbnb* (Sundararajan, 2014), hosts are not eligible for unemployment benefits and other worker-related governmental programs (Chen et al., 2020). Hence, *Airbnb* as a platform could transfer their risk to *Airbnb* hosts, who experienced losses around 6.5 times greater than the platform itself (Chen et al., 2020; Friedman, 2014). The hosts' income loss further influences potential mortgage payments and other debts and increases the variance of hosts' income (Chen et al., 2020).

Farmaki et al. (2020b) used a qualitative approach and conducted a semi-structured interview with hosts of peer-to-peer accommodation to examine perceived short-term impacts of the pandemic, how the hosts dealt with the challenges, and the perceived long-term impacts of the pandemic. Concerning short-term impacts, all hosts experienced a direct negative impact by governmental intervention to minimize the spread of SARS-CoV-2. They further described an increase in cancellations and a decrease in bookings. As peer-to-peer renting is the first source of income for some hosts, their economic situation experienced a severely negative impact. The effects were even worse for professional hosts as they had to continue paying cleaners and other staff. Hosts described lowering prices to stimulate demand, target domestic tourists, minimize human contact through self-check-in, and improve cleaning.

This paper wants to analyze the switch from short-term to long-term renting, as well as renting of entire properties instead of shared apartments. Furthermore, this paper aims to investigate the factors that determine the probability of an *Airbnb* listing being active before and during the COVID-19 pandemic.

## 3. Methodology

## 3.1. Sample definition

The platform *Inside Airbnb* provides big data on *Airbnb* listings for Berlin (*Inside Airbnb*, 2021). The unemployment rate is taken from the Federal Statistical Office (Statistisches Bundesamt, 2021). The Mitteldeutscher Rundfunk (MDR) and the German Foreign Office provide data about lockdowns and travel restrictions implemented during the COVID-19 pandemic (Mitteldeutscher Rundfunk, 2021; Auswärtiges Amt, 2021).

The cleaned monthly panel data for Berlin consists of 326,226 observations and covers the period from 2019 to 2020. In total there are 19,897 *Airbnb* listings. In the COVID-19 phase 123 hosts entered the market while 5,016 hosts left the market.

We subdivide the researched period into two major phases: The pre-pandemic phase begins on January 1st, 2019, and ends on December 31st, 2019. The COVID-19 phase begins at the 4th of January 2020 - the World Health Organization (2020) tweeted that there was a cluster of pneumonia cases in Wuhan, Hubei province, People's Republic of China - and ends on December 31st, 2020. This means we have almost the same amount of time in both phases.

## 3.2. Variables

*Overview Inside Airbnb*

The platform *Inside Airbnb* provides data on numerous characteristics of *Airbnb* listings such as price per night, room type with the characteristic entire home/apartment or private room, the minimum number of nights for a booking, date of the last review, number of monthly reviews - which is a moving average -, number of overall reviews, number of days available for booking within one year, and numerous other factors.

The dependent variable *airbnb* is binary and takes the expression 1 if a listing *i* is active on *Airbnb* at time *t* and 0 when the opposite is the case. In addition, the dichotomous variable takes the value 0 if the last review of an *Airbnb* listing was at the most twelve months ago. The categorical variable *entire* is based on the room type, taking on the value 1 if the whole apartment is rented and 0 if otherwise. The categorical variable *long* differentiates between short-term and long-term rentals to determine a possible change in trend. All *Airbnb* listings that require a minimum of 60 nights per booking are labeled as long-term options. Long term options take the value 1, short term options take the value 0. A host's *income* from an *Airbnb* accommodation is measured on a ratio scale and derived from the components of price per night, required minimum number of nights per booking, and moving average number of reviews per month which serves as a proxy variable for the number of bookings per month (*Airbnb*, 2021). For our estimations, we use the variable *host_income_diff* which represents the differences in a host's income between the respective time periods. Lockdowns are periods with massive restrictions, for instance, in the form of curfews and closures. The categorical variable *lockdown* takes on the value 1 if a lockdown in the sense of the above definition is detected on at least 15 days of the respective month. This determination is based on the reporting of the MDR. In this sense, the variable *lockdown* takes on the value 1 for April, October, November, and December 2020 for Berlin. Travel restrictions are existing in the case of complete closure of the German borders on at least 15 days of the respective month, or in the case of a ban on tourist entry on at least 15 days of the respective month. The categorical variable *travel_restrictions* takes on the value 1 if such are in operation is executed by the government. The former applies to March, April, and May 2020, while the latter case occurs for November and December 2020. The German Foreign Office and MDR reporting provide the basis for defining this variable (Auswärtiges Amt, 2021; Mitteldeutscher Rundfunk, 2021).

As a control variable for business cycles, we choose the rate of unemployment which was collected monthly at the national level. The source of this data is the Federal Statistical Office, with its publicly accessible GENESIS-Online database (Statistisches Bundesamt, 2021).

## 3.3. Descriptive statistics

Besides listing-specific data, pandemic-related factors such as *lockdown* and *travel_restrictions* as well as the macroeconomic factor *unemployment* are assigned to every *Airbnb* listing in all 24 time points. In addition, the binary variable *airbnb* describes if an *Airbnb* listing is active or not at the respective time. The large values of the standard deviation indicate that the selected sample is heterogeneous concerning the time dimension. Table 1 summarizes descriptive statistics for the pre-pandemic period with 195,360 observations. Table 2, in contrast, provides descriptive statistics with 130,866 observations for the COVID-19 phase.

Table 1 – Summary Statistics of Pre-Pandemic Phase

|  | n | mean | sd | min | max |
|---|---|---|---|---|---|
| airbnb | 195,360 | 0.652 | 0.476 | 0 | 1 |
| availability_365 | 195,360 | 72.062 | 112.417 | 0 | 365 |
| entire | 195,360 | 0.499 | 0.500 | 0 | 1 |
| host_income | 195,360 | 158.865 | 451.620 | 0 | 15,891.600 |
| host_income_diff | 195,360 | 0.795 | 160.880 | -9,699 | 13,737.800 |
| lockdown | 195,360 | 0 | 0 | 0 | 0 |
| long | 195,360 | 0.029 | 0.168 | 0 | 1 |
| minimum_nights | 195,360 | 4.682 | 8.594 | 1 | 62 |
| monthly_reviews | 195,360 | 0.979 | 1.424 | 0.010 | 30 |
| number_of_reviews | 195,360 | 26.592 | 47.651 | 1 | 626 |
| price | 195,360 | 51.842 | 26.164 | 0 | 137.000 |
| travel_restrictions | 195,360 | 0 | 0 | 0 | 0 |
| unemployment | 195,360 | 5.004 | 0.170 | 4.800 | 5.300 |

Source: Own Estimation based on data from Auswärtiges Amt (2021); *Inside Airbnb* (2021); Mitteldeutscher Rundfunk (2021); Statistisches Bundesamt (2021); and World Health Organization (2021) and visualized with Stargazer Package for R Studio (Hlavac, 2018).

Table 2 – Summary Statistics of COVID-19 Phase

|  | n | mean | sd | min | max |
|---|---|---|---|---|---|
| airbnb | 130,866 | 0.504 | 0.500 | 0 | 1 |
| availability_365 | 130,866 | 75.222 | 119.938 | 0 | 365 |
| entire | 130,866 | 0.524 | 0.499 | 0 | 1 |
| host_income | 130,866 | 145.844 | 477.555 | 0 | 23,889.600 |
| host_income_diff | 130,866 | -3.409 | 217.013 | -22,337.280 | 22,265.280 |
| lockdown | 130,866 | 0.327 | 0.469 | 0 | 1 |
| long | 130,866 | 0.032 | 0.177 | 0 | 1.000 |
| minimum_nights | 130,866 | 4.997 | 9.019 | 1 | 62 |
| monthly_reviews | 130,866 | 0.836 | 1.289 | 0.010 | 30 |
| number_of_reviews | 130,866 | 35.051 | 59.687 | 1 | 950 |
| price | 130,866 | 52.687 | 26.671 | 0 | 137.000 |
| travel_restrictions | 130,866 | 0.456 | 0.498 | 0 | 1 |
| unemployment | 130,866 | 5.807 | 0.425 | 5.100 | 6.400 |

Source: Own Estimation based on data from Auswärtiges Amt (2021); *Inside Airbnb* (2021); Mitteldeutscher Rundfunk (2021); Statistisches Bundesamt (2021); and World Health Organization (2021) and visualized with Stargazer Package for R Studio (Hlavac, 2018).

## 3.4. Economic model

The research work at hand uses a binary response model, i.e. a probit model, to explain the effects of the independent variables $x_j$ on the response probability P ($airbnb = 1 | x_j$), corresponding to an active listing if *airbnb* takes on the value 1 and an inactive listing if *airbnb* takes on the value 0.

The probit model used in this paper contains listing-specific, pandemic-related, and a macroeconomic factor:

$$airbnb_{it} = \phi(\beta_0 + \beta_1 host\_income\_diff_{it} + \beta_2 entire_{it} + \beta_3 price_{it}$$
$$+ \beta_4 long_{it} + \beta_5 number\_of\_reviews_{it} + \beta_6 lockdown_{it}$$
$$+ \beta_7 travel\_restrictions_{it} + \beta_8 unemployment_{it} + \pi_i + \delta_t + \varepsilon_{it})$$

(1)

Where *airbnb* is the dependent variable taking on the value 0 if an *Airbnb* listing *i* is inactive at time *t* or the last review has been written at least 12 months ago. The difference of host's income between period *t* and *t-1* is captured by the variable *host_income_diff*. Furthermore, *entire* is a categorical variable taking on the value 1 if the entire apartment is subleased and 0 if only a private room is subleased. The variable *price* is the price per night; *long* is a categorical variable taking on the value 1 if the minimum stay is at least 60 days and 0 if otherwise; *number_of_reviews* is a variable indicating the total number of reviews and being a proxy variable for the length of this listing being active on *Airbnb*. Factors concerning the COVID-19 pandemic are captured by the variables *lockdown*, which is a categorical variable taking on the value 1 if there is a lockdown and 0 if otherwise; and *travel_restrictions*, which is a categorical variable taking on the value 1 if there are travel restrictions and 0 if otherwise. Macroeconomic changes are included with the variable *unemployment*, referring to the unemployment rate to control for business cycle effects; $\pi_i$ is a random effects listing-specific error term; $\delta_t$ is a fixed effects time-specific error term. Finally, the error term, $\varepsilon_{it}$, represents all disturbances.

## 4. Empirical analysis

## 4.1. Descriptive analysis

Before conducting a paired two-sample t-test for means, the average of the respective variables during the pre-pandemic phase as well as the COVID-19 phase is calculated for each host in our data set. Consequently, means in Table 3 differ from the respective variables' means in Table 1 and Table 2. Furthermore, the variables *host_income*, *entire* and *long* were rounded to two decimal places in advance. Additionally, observations that only have data for the pre-pandemic phase but not for the COVID-19 phase have been excluded from the descriptive analysis. Table 3 shows the results of our paired two sample t-tests for means. First, we conclude that host's income is significantly lower in the COVID-19 phase compared to the pre-pandemic phase. Second, we show that more entire accommodations are rented during the COVID 19 phase. Third, we provide evidence for a statistically significant higher number of long-term rentals in the COVID-19 phase.

Table 3 – Results of Paired Two Sample t-tests for Means

| Paired Two Sample t-Test for Means | | |
|---|---|---|
| Hypothesized Mean Difference: 0 | | |
| *host_income* by phase | pre-pandemic phase | COVID-19 phase |
| Mean | 162.552 | 145.375 |
| Observations | 13,715 | 13,715 |
| t statistic, p value | 7.144 [0.000] | |
| *entire* by phase | pre-pandemic phase | COVID-19 phase |
| Mean | 0.509 | 0.513 |
| Observations | 14,758 | 14,758 |
| t statistic, p value | -5.27623 [0.001] | |
| *long* by phase | pre-pandemic phase | COVID-19 phase |
| Mean | 0.02988 | 0.03152 |
| Observations | 14,758 | 14,758 |
| t statistic, p value | -2.60263 [0.001] | |

Source: Own Estimation based on data from *Inside Airbnb* (2021) and World Health Organization (2020).

## 4.2. Results and data evaluation

Table 4 shows the average marginal effects on the dependent variable *airbnb*. We first show the partial effects of the analyzed variables. Thus, specifications (1) to (8) include only one variable to show its individual effect, whereas the preferred model specification (9) shows the partial marginal effects of several variables simultaneously. We estimate the panel probit model using maximum likelihood with clustered standard errors and we report average marginal effects.

Table 4 – Model Specifications for *Airbnb* Listings

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| *host_income_diff* | 0.000*** | | | | | | | | |
| | (0.000) | | | | | | | | |
| *entire* | | 0.048*** | | | | | | | 0.048*** |
| | | (0.007) | | | | | | | (0.007) |
| *price* | | | 0.003*** | | | | | | |
| | | | (0.000) | | | | | | |
| *long* | | | | 0.092*** | | | | | 0.074*** |
| | | | | (0.024) | | | | | (0.024) |
| *number_of_reviews* | | | | | 0.011*** | | | | |
| | | | | | (0.001) | | | | |
| *lockdown* | | | | | | -0.129*** | | | -0.071*** |
| | | | | | | (0.003) | | | (0.002) |
| *travel_restrictions* | | | | | | | -0.118*** | | |
| | | | | | | | (0.002) | | |
| *unemployment* | | | | | | | | -0.109*** | -0.089*** |
| | | | | | | | | (0.003) | (0.002) |
| Observations | 283,632 | 283,632 | 283,632 | 283,632 | 283,632 | 283,632 | 283,632 | 283,632 | 283,632 |
| Pseudo R² | 0.000 | 0.002 | 0.023 | 0.000 | 0.217 | 0.006 | 0.006 | 0.009 | 0.009 |

Significance Levels: Standard errors are in parentheses. * $p<0.10$; ** $p<0.05$; *** $p<0.01$.
Source: Own Estimation used maxLik Package for R Studio (Henningsen & Toomet, 2011) based on data from Auswärtiges Amt (2021); *Inside Airbnb* (2021); Mitteldeutscher Rundfunk (2021); Statistisches Bundesamt (2021); and World Health Organization (2021).

Our results show that marginal effects for listing-specific explanatory variables are statistically significant but close to zero: *Host_income_diff, entire, price, long,* and *number_of_reviews* have a statistically significant positive marginal effect on the probability of an *Airbnb* listing being active. *Lockdown* and *travel_restrictions* influence the probability of an *Airbnb* listing being active significantly negatively, showing that the measurements against the spread of SARS-CoV-2 taken by the government significantly influenced the shared housing market. Moreover, the marginal effect of *unemployment* is negatively correlated with an *Airbnb* accommodation being active.

Our preferred model specification (9) in Table 4 shows the marginal effects of the variables *entire*, *long*, *lockdown*, and *unemployment* simultaneously on the probability of an active *Airbnb* listing. Also in this specification *entire* and *long* have a positive and statistically significant effect on the probability of an *Airbnb* listing being active. This means that renting out whole apartments or houses, and renting long term increases the probability of an Airbnb listing to remain in the market. On the other hand, as expected, *lockdown* has a statistically significant influence and decreases the probability of an active *Airbnb* listing, whereas *unemployment* does so too.

## 4.3. Robustness analysis

The following section aims at testing the robustness of our model. To account for differences between the influence of a lockdown in Germany and solely travel restrictions, we run two regressions using the variable *lockdown* and secondly, the variable *travel_restriction*. Moreover, we test for the quality of *Airbnb Listing by differentiating between accommodations with a low number of reviews and accommodations with a high number of reviews. Finally,* we subdivide our original panel data set into data for the pre-pandemic phase and data for the COVID-19 phase to examine if the effects of the variables *long* and *entire* change when only considering the COVID-19 phase.

Table 5 – Specifications with the Variable *lockdown* versus *travel_restrictions*, *low number of reviews* versus *high number of reviews,* and the *pre-pandemic phase* versus *COVID-19 phase*

| | (1) with lockdown | (2) with travel-restriction | (3) low number of reviews | (4) high number of reviews | (5) pre-pandemic phase | (6) COVID-19 phase |
|---|---|---|---|---|---|---|
| *entire* | 0.047*** | 0.047*** | 0.014* | 0.039*** | 0.036*** | 0.126*** |
| | (0.007) | (0.007) | (0.008) | (0.007) | (0.007) | (0.008) |
| *long* | 0.073*** | 0.073*** | 0.258*** | -0.119*** | -0.022 | -0.013* |
| | (0.024) | (0.024) | (0.033) | (0.033) | (0.018) | (0.021) |
| *lockdown* | -0.130*** | | -0.119*** | -0.057*** | | -0.047*** |
| | (0.003) | | (0.003) | (0.002) | | (0.002) |
| *travel_restrictions* | | -0.119*** | | | | |
| | | (0.002) | | | | |
| *unemployment* | | | -0.156*** | -0.057*** | | |
| | | | (0.004) | (0.003) | | |
| Observations | 283,632 | 283,632 | 147,439 | 136,193 | 195,360 | 283,632 |
| Pseudo R$^2$ | 0.007 | 0.008 | 0.041 | 0.021 | 0.001 | 0.013 |

Significance Levels: Standard errors are in parentheses. * p<0.10; ** p<0.05; *** p<0.01.
Source: Own Estimation used maxLik Package for R Studio (Henningsen & Toomet, 2011) based on data from Auswärtiges Amt (2021); *Inside Air*bnb (2021); Mitteldeutscher Rundfunk (2021); Statistisches Bundesamt (2021); and World Health Organization (2021).

Results in Table 5 in specification (1) and (2) show that the marginal effects of *long* and *entire* remain positive and statistically significant for both specifications, the one with *lockdown* and the one with *travel_restriction*. We observe that *lockdown* has a slightly more negative effect on the probability of an *Airbnb* listing being active than *travel_restrictions*. Nevertheless, because of almost identical effects it is irrelevant which of the two variables is used in our preferred specification (9) in Table 4.

Results in Table 5 in specification (3) and (4) show the results when controlling for the quality of *Airbnb listings*. The results indicate that the coefficient of the variable entire is positive and statistically significant at the 10% level for *Airbnb* listings with a low number of reviews, and positive and statistically significant at the 1% level for *Airbnb* listings with a high number of reviews. The coefficient of the variable long is positive and statistically significant at the 1% level for *Airbnb* listings with a low number of reviews, whereas it is negative and statistically significant at the 1% level for *Airbnb* listings with a high number of reviews. The latter result is counter intuitive. For both subsamples, the estimates of *unemployment* and *lockdown* remain negative and statistically significant on a significance level of 1%.

Results in Table 5 in specification (5) and (6) show the results when differentiating between the pre-pandemic phase and the COVID-19 phase. The results show a statistically significant positive marginal effect for the variable *entire*, mainly insignificant marginal effects for the variable *long*, and statistically significant negative effects for the variable *lockdown*. However, between the pre-pandemic phase and the COVID-19 phase, the marginal effect of the variable *entire* increases. Therefore, renting an entire apartment in the COVID-19 phase increases the probability of an active *Airbnb* listing by a higher value than in the pre-pandemic phase.

## 5. Discussion and conclusion

Our Big Data analysis using a probit model supports the assumption that the Sharing Economy experiences a structural change during the spreading of SARS-CoV-2. Our key findings are that host who rented entire apartments and long-term options had a higher probability to stay in the market. Moreover, it could be shown that the lockdowns and travel restrictions harmed the sharing economy. Finally, the business cycle, proxied with the *unemployment rate*, also influenced the sharing economy.

Nevertheless, this does not mean the end of the sharing economy. Our results could help future policies better adapt to the sharing economy by providing insight into the behavior of its participants. However, more future research is needed as it is unclear how SARS-CoV-2 mutates, which policies for social distancing will be in place in the future, and if the structural change we found is long-term and sustainable.

As with all research, our work is not free from limitations. First of all, the COVID-19 pandemic is a very recent phenomenon, and we are still in the middle of its occurrence. As a result, only vague assumptions about further developments can be made. Moreover, the *Airbnb* platform and hosts are shaped by the media and thus short-term events. The actuality of the subject means that the research field offers much potential, and current studies are usually not yet peer-reviewed, so their quality must be viewed critically. In addition, a comparison with other pandemics is problematic, as the last global pandemic on a comparable scale was the Spanish Flu in 1918. At that time, tourist travel was much less pronounced, and the sharing economy was non-existent. Also, no comparable relevant data can be found for economic changes during the Spanish Flu.
In terms of data selection, this paper is limited to the geographic area of Germany and covers only the city of Berlin. Thus, it remains unclear whether the effects examined would also be confirmed in more rural areas, or instead exclusively arise in urban areas. In addition, our research only compares the years 2019 and 2020. Adding other pre-pandemic phases could have minimized cyclical fluctuations and thus provided more reliable results.

Future research should consider and minimize the limitations of this paper. For example, the data set could be extended to the entire European region and thus compare countries affected differently by the pandemic. In this course, the influence of the 7-day incidence rate or media coverage would also be of interest.

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