The impact of Airbnb on local labour markets in the hotel industry in Germany

- working paper -

Ana-Maria Suciu, Joint European Master Programme in Comparative Local Development, 2014-2016

First draft upload: November 23, 2016

Abstract

Looking at "the sharing economy", the paper tackles its impact on employment, in the context of traditional businesses being challenged by innovative business models. The focus is on the way Airbnb, a major sharing economy player in the tourism industry, affects local labour markets. I am looking at 20 German cities and check how the presence of Airbnb impacts the hotel industry workers. Researching the period 2010 - 2014 and knowing Airbnb started their business in Germany in 2012, I investigate whether there are changes in the number of employees in the two time periods for two groups of cities, one with high Airbnb penetration and one with lower Airbnb penetration. Then I look at changes in employment type and wage effects. The results show that both employment and employment type are stable, no significant changes occurring after 2012. A third hypothesis regards wages in the hotel industry. Using a difference in difference strategy, with Airbnb as treatment, I estimate a small negative effect on daily wages for cities in which Airbnb presence is higher and after 2012 – from 2% to 6% lower daily wages. The effect is slightly higher for small medium entities and for full-time workers.

Executive Summary

In this paper, I look at the way Airbnb affects the employment in the hotel industry in Germany. Airbnb is an American company established in 2008 in San Francisco, US. It is an online market place for short-term accommodation, where private individuals (called hosts) can rent spare rooms or entire apartment for tourists. Airbnb is a poster child of the sharing economy and there is much debate in the media regarding its effects on neighbourhoods, economy and even the labour market. While there is no public data in regard to how much income an Airbnb rental generates, media approximations lead to the idea that the earnings are not to be neglected (Crain's Chicago Business, 2015). The hotel industry itself claims that Airbnb affects their revenue while providing illegal hotel services (HVS Consulting & Valuation, 2015; Hotrec, 2015). Thus, it is likely that Airbnb is a true competitor of the hotel industry.

Study problem

As Zervas et. al (2016) show, high Airbnb availability has effects on hotel revenue and those effects are mostly felt by low-price hotels and hostels. This is enough evidence to support hypotheses related to similar effects on the labour market, once the hotel industry faces revenue loss. The study problem is related to the effect of Airbnb on the employment in the hotel industry, operationalized in three different ways, which lead to 3 hypotheses:

H1: Higher Airbnb penetration rates correlate with less employees in the hotel industry.

H2: Higher Airbnb penetration rates correlate with less full time employees in the hotel industry.

H3: Higher Airbnb penetration rates correlate with smaller daily wages in the hotel industry.

Methodology

The unit of analysis is urban level in Germany. Given that data on Airbnb listings is not available for all cities, I analyse 20 cities for which such data is available. I construct an Airbnb penetration score which computes the number of listings per 100.000 population in each city. Based on this score, I split the 20 sample cities in 2 groups, considering one group received the Airbnb treatment (they have more than 80 Airbnb offers/100.00 population) and the other group serves as a control group. The 20 cities are: Berlin, Hamburg, Munich, Cologne, Frankfurt, Stuttgart, Dusseldorf, Dortmund, Essen, Bremen, Leipzig, Nuremberg, Dresden, Hannover, Duisburg, Bochum, Wuppertal, Bielefeld, Bonn and Munster.

In order to identify sectoral effects of Airbnb on employment, I use different approaches for each hypothesis to be tested. The first hypothesis, regarding employment in the hotel industry, is tested by using descriptive statistics and OLS regression with hotel employment per city as dependent variable

and Airbnb penetration score as the main predictor, then adding control variables for robustness checks. For the hypothesis regarding employment type, I use Probit regression, where full-time employment is computed as 1 and the other types of employment as 0. For the daily wage variation, I use a difference-in-differences strategy, where the outcome variable is the daily wage of a person employed in the hotel industry in a given city, at a given time. The treatment is the availability of Airbnb offers and the two groups consist of workers in the cities selected before (cities with high and low Airbnb penetration rate). The two points in time for which the hypothesis will be tested against are 2010 -2012 (before Airbnb) and 2013 - 2014 (post-Airbnb).

Findings

Airbnb and employment in the hotel industry

The changes in absolute numbers of employees in the hotel industry show that in cities with a higher Airbnb penetration scores more people are employed in the hotel industry then in cities with lower Airbnb penetration score. The correlation coefficient between employment in the hotel industry and the Airbnb penetration score is strong and positive. In order to check the correlation between employment in the hotel industry after the Airbnb emergence, I used OLS regression in which hotel employment in 2014 is the dependent variable and the independent variables are the Airbnb Penetration score, the share of hotel employment of the total employment in 2011 (as in indicator for tourism size and considering that a shrinking or growing tourism market would affect employment some years later) and population. The results show a significant positive effect of Airbnb penetration score when considered alone and when considered in a model in which we control for the population. However, once we introduce the share of employment in hotels from total employment, the Airbnb factor loses its significance. While not robust, the results do show that there is a positive relation between the number of Airbnb offers and the employment in the hotel industry.

Employment structure and Airbnb

The Probit regression models show that Airbnb penetration scores have a positive effect on employment type. Therefore, in cities with a high Airbnb penetration, full-time employment is more frequent. The effect size is very small, but highly significant throughout the six tested models. The same tendencies in terms of significance are present when we look at population and the size of the hotel industry, although the results show both positive and negative effects when we add factors into the regression models. The explanation may be the fact that bigger cities, with more hotels, may tend to employ more people full-time, but also more seasonal workers and marginal part-time workers, thus the effects being unclear. City level unemployment has a steady negative impact on the type of employment, while education always has a positive effect. Age positively affects the probability of being full-time employed, but when we control for gender (counted as 1 if the employee is male), the effect is negative. Establishment size does not seem to affect employment type, the results not being significant. In conclusion, in cities with more Airbnb, the probability of workers in the hotel industry being in full-time employment is higher than in the cities with less Airbnb offers.

Airbnb effect on wages in the hotel industry

The first model tested shows that being in the treatment group and in the second time period negatively impacts the daily wage. While the coefficient is not significant when only DiD estimators are factors in the regression, once control variables are added, they become significant at 0.01 level. When controlling for population and tourism size, the results show that workers in the hotel industry in the cities with more Airbnb and after 2012 earn 3,3 euros less per day then workers in the same sector in cities that have less Airbnb presence. As factors are added in the regression, the values decrease. The factors that have the biggest effect on wages are the employment type, education and gender. The time effect is positive and significant (wages increase with time), but after controlling for education and age they become negative and insignificant. The treatment estimator (being in a city with more Airbnb) is always positive and significant, which shows that cities with more Airbnb presence have, on average, higher wages in the hotel sector. Population has a negative impact on wages in the hotel industry on average. The tourism sector size has a positive effect on wages, the more nights spent in the touristic accommodations, the higher the salary. Unemployment has a negative effect on wages and age a positive, but rather small one. The size of the company has a small and less significant positive effect on daily wages.

When testing the same models with log of daily wages, the specific effect of being both in the treatment group and after 2012 on the daily wage varies between -2% and -7%. The regression results on full-time employees' daily wages follow the same trends as the ones on all hotel workers, but are a little stronger. In absolute terms, the effect of the Airbnb intervention (when an employee is both in the treatment group and after 2012) account for between 96 eurocents and 4.3 euros a day, all statistically significant at 0.01, but in percentages, the proportions of 1% to 6% decreases of the daily wage are kept.

Introduction

The rise of digitalization and online two-sided marketplaces bring about changes in our everyday lives. We travel long distance by BlaBlaCar, staying in an Airbnb room instead on an hotel and using Uber instead of taxis. We can now use apps to find a pet sitter while we are on vacation, to find a person to do our chores or home repairs, to swap clothes or to share food. Similarly, companies use online platforms like UpWork or Amazon Mechanical Turk, where people from all over the world, from high to low skilled, offer their services. These people, potentially from a global South country, will do the task without the bureaucracy of employment and for much less money (Agrawal et. all, 2013). It seems like a win-win for all parties involved, some get cheaper services and some get to make extra income in their free time, the platforms just match supply and demand and take a commission for it. However, the effects of the platform society on labour markets should not be neglected: work that goes digital could eventually be a displacement/replacement or shift from a former full-time job with all benefits and perks that came with it. It may also be the case that digitalization creates new jobs, as new services and products are developed (Degryse, 2015, p. 5-6). However, when people choose to go to a digital platform in order to find work, it is likely that they either do not earn enough or they are unemployed, part-time employed or self-employed (Degryse, 2015, p. 5-6; Irani 2015). What was once a bundle of tasks made into a job it can become disintegrated and sold as 'micro-jobbing' to a global crowd willing, probably in the absence of better solutions, to work multiple such micro-tasks in order to make ends meet. There are some perks with this type of working: flexible hours, work only when you need and the types of tasks you enjoy etc., which makes it appealing to people (Degryse, p. 35, 2015). With so many potential effects, digitalization and platform economy effects on the labour markets is an interesting research field. While it is still a marginal phenomenon, digitalization and platform economy is expanding at a rapid pace. A Price Waterhouse Cooper research shows that in February 2015 Uber alone was valued at 41.2 billion $ and estimations for the whole "sharing economy" sector is that from a 15 billion $ now it will get to 335 billion $ by 2025, which would be half of the traditional rental market value across sectors (PWC, 2015).

Digitalization trends and platform capitalism affect labour markets in at least two ways. First, by competing with established industry, the new 'sharing'/on-demand economy business models may have an effect on the employment in certain industries and such effect could be negative (Degryse, 2015). The potential consequences are: decreases in employment in hotel industry due to Airbnb availability; decreases in employment in taxi or car-for-hire industry due to Uber; replacement of full-time employment with alternative, more precarious forms of employment; taxation issues etc. Second, the exclusively online labour marketplaces using crowdsourced labour like Amazon Mechanical Turk, upWork or CloudFactory, could reshape the global labour market, by matching a global supply of work with the demand, and thus affecting formal employment practices (workers are contractors not employees), wages (workers from less developed countries can afford to work for smaller wages), taxation (it is unclear how fair taxation obligations can be enforced and on whom should they be enforced) (Agrawal et. all, 2013). Online labour markets can also contribute to decreasing formal employment in some industries.

While all of them matching supply and demand and increasing the use of idle resources including labour, there are several distinct characteristics of the on-demand businesses. The first distinction is between services delivered offline, in a specific location (pet sitting, driving, providing accommodation etc.) and online labour markets in which demand meets a global supply of workers and the work itself is supplied online. Another differentiating criterion is related to the capital needed in order to deliver the work. We can distinguish between jobs that require a high capital investment or ownership (a house to rent on Airbnb, a car to drive for Uber) and low capital investment or ownership (you need a computer and an internet connection to provide services on Elance and you need some tools to provide services on Hellocasa.fr). Depending on the capital goods ownership level, the main service is either renting (which requires less amount of work), or service delivery per se (driving, fixing someone's plumbing issues, entering data into a database etc. – which require mostly work). Then there are differences in the way platforms set the value of work (through a defined payment/unit of task like Uber or through bidding for jobs and the lowest price wins, like it happens on TaskRabbit).

In this paper, I look at the way Airbnb affects the employment in the hotel industry in Germany. Airbnb is an American company established in 2008 in San Francisco, US. It is an online market place for short-term accommodation, where private individuals (called hosts) can rent spare rooms or entire apartment for tourists. Airbnb is a poster child of the sharing economy and there is much debate in the media regarding its effects on neighbourhoods, economy and even the labour market. While there is no public data in regard to how much income an Airbnb rental generates, media approximations lead to the idea that the earnings are not to be neglected (Crain's Chicago Business, 2015). The hotel industry itself claims that Airbnb affects their revenue while providing illegal hotel services (HVS Consulting & Valuation, 2015; Hotrec, 2015). Thus, it is likely that Airbnb is a true competitor of the hotel industry. By now, Airbnb is present in more than 34,000 cities and 191 countries (Airbnb website, 2016), which makes it one of the biggest “sharing economy” corporations worldwide.

The choice of narrowing down the research to one sector and one sharing business has its advantages. First, by only looking at the biggest sharing company the hotel industry consistency in data gathering is assured. Second, the effects studied are very specific in terms of employment: did the number of employees in the traditional sector increase?; Did the forms of employment change? Are there wage effects?. Third, we can look at specific policies targeted towards short-term rentals and discuss their impact narrowly. Having specific research questions, even if only in one sector, has the advantage of better operationalizing variables and test very specific hypotheses, which leads to specific industry insights and help policy makers in developing better regulations in this area.

However, focusing only on one sector has disadvantages. Generalizations regarding the sharing economy overall are excluded. Then, as stated above, the sharing economy is a very diverse field. By only looking at a platform that consists of sharing assets, we do not look into how sharing economy affects workers within this sector, but only effects on traditional businesses.

The first chapter of the paper provides a general theoretical background on digitalization and how we define the sharing economy as a part of the digitalization processes. The second part looks at empirical research on the sharing economy effects at global and local levels, focusing mostly on Airbnb related research. The third part is a description of the project work and the methodology used. The remaining chapter is the empirical analysis of Airbnb effects on labour markets in Germany.

1. Theoretical background

Digitalization effects on economy and society

The literature on digitalization effects on economics and society in general is divided between long-term approaches (focusing on computerization, automation, replacement of labour by computers) and short-term approaches. They are related to the platform society in which global middle-men, through online platforms and algorithms, provide access to either goods or services, and those goods and services may come from businesses or individuals. There are several attempts of placing the digital revolution in an historical context of industrial revolutions, as the Fourth Industrial Revolution, thus the name Industry 4.0 or Labour 4.0. Kowalski (2015) considers the steam engine as the first industrial revolution, followed by electrification and mass production, the computer and now the digital revolution. Huws (2013) places the digital revolution in the context of the last century's evolution of labour dynamics: the period between 1940's and 1973 – with the emergence of welfare states, national economies and establishing workers' rights; the period after the oil crisis of '73 until late 80's – characterized by the rise of multinational companies, outsourcing work in developing countries, low paid jobs mainly for women and migrants but still rather strong unions and work as formal contractual agreements; from 1990 to 2000 labour relations deregulated, unions lost bargaining power, neoliberal practices led to mass privatizations and, in the process, employment protection was reduced; by 2000 we are already in the 'Internet Age', in which ICT was an integrating part of all work and some of the work begins to take place online.

Kowalski (2015) states that digitalization is characterized by a spectacular increase in productivity and a great impact on employment and work. While the productivity increases at global level, the number of available jobs is decreasing – or it is replaced by other types of jobs, displaced or shifted. In any case, digitalization highly affects labour markets and work as we know it. The author distinguishes between the digital transition of traditional industries and services and the outsourcing of digital activities (crowdworking, clickworking etc.). As stated above, the thesis project will look into the digital transformation of traditional sectors, namely the hotel industry. However, the literature on crowdwork and clickwork is equally essential when we talk about labour regulations and changes in employment due to digitalization.

In terms of automation and replacement of labour, Frey and Osborne (2013) analyse the probability of computerization for 702 occupations in the US labour market. According to their predictions, 47% of the whole employment in the US is at risk of automation in the near future (the next two decades). Using Frey and Osborne's methodology, Bruegel, a think tank in Brussels, found that across EU the risk of automation is even higher, with an average of 54% of the total employment being at risk (Bruegel blog, 2016). The model, however, does not account for the capacity of either US or Europe to achieve automations, which requires high investments in infrastructure for companies and which may prove a deciding factor on how long it will take for automation to happen. While the probability of replacement of labour by machines can be high on the long run, the high-speed internet connection, the Big Data and new forms and mobile devices lead to a new economy and a new labour market as we speak (Degryse, 2016, p. 8). At the same time, other authors show that such pessimistic view on labour effects of digitalization are not realistic. Arntz et. al (2016), using a task-based approach to automation, find that in 21 OECD countries 9% of the jobs are in risk of automation (Arntz et.al, 2016).

Degryse (2016) identifies four major impacts of digitalization on labour markets: job creation – as new sectors, services and products appear; job change – the use of applications and machines change the nature of jobs; job destruction – due to automation; and job shifting – which comes with digital platforms, crowdwork, on-demand work and the sharing economy.

When it comes to crowdwork, the literature is quite rich in experiments in online labour markets, as these workers are easily accessible if you act as an employer. Using oDesk data, Agrawal et.al (2013) show that by late 2012 there were 10 times more employers from high-income countries than from low-income countries on the platform, while there were 4.5 more contractors from low-income countries than from high-income countries. This finding suggests that as labour markets globalize, at least some of the jobs would be crowdsourced towards low-income countries, affecting local labour markets in both low-income and high-income countries (in different ways).

In the context of this paper, some of these effects are considered. Degryse's four effects, job creation, job change, job destruction and job shifting could be present when we consider the case of Airbnb and tourism sector. As Airbnb disrupts the hotel industry and potentially decreases the hotels' revenues, it may be a case of job destruction – although not due to automation, but due to competition from digital native companies. On the other hand, there could be some job creation due to Airbnb, private individuals renting on Airbnb hiring cleaning staff for their Airbnb apartments. However, so far, literature focused more on employment within the digital economy than on effects on traditional employment due to digitalization. As Degryse notices: “These companies concentrate exclusively on their core business which consists in linking up supply and demand, disclaiming all other types of responsibility or commitment. As we have seen, Upwork offers the services of more than 10 million workers but refuses to regard itself as an employer. Similarly, Airbnb (or Uber) has become one of the largest accommodation (or transport) services in the world without owning a single room (or fleet of vehicles), without exercising the least contractual, legal or penal liability in its mediation service, and with a minimum of salaried staff. Airbnb, Uber, Upwork have no more than a few hundred direct employees.” (Degryse, 2015, p. 34). Thus, the discussion is more on how these companies employ people than the effect of their competition on the traditional business sectors.

Another important theoretical aspect of the sharing economy regards regulations and policy issues. While the examples and questions are numerous, I will focus the regulatory theoretical approach on short-term rentals only. The regulatory frameworks for Airbnb and similar short term rental businesses are still lacking good practice models and the existing regulations leave room for abuse. Miller (2014) envisions a legal framework in which short term rentals could function. First, all citizens get a ‘transferable sharing right (TSR)’ to rent their owned space for short term rentals. In order to access this right, citizens have to go through an online platform of the city where they fill out information about the usage of the right (the period, the price, the location etc.) and pay a fee (which would help the city solve issues coming from the externalities of the short term rental market). The right is transferable in the sense that it is not connected with a certain location, thus those who don’t want to use the right can sell it to those who want to, thus creating a city-controlled market for TSRs. If this market is properly designed, there will be surplus in the area where tourists do not want to stay and scarcity in the popular touristic areas, which, as Miller claims, enables the rest of the marketplace to benefit from the short-term rental industry. Miller raises concerns about potential TSR issues that might arise (issues between owners and renters, potentially forbidding renters to access their TSR rights are to be taken care of; effects on the hotel industry should be counter balanced through redirecting part of the TSR fee towards those workers affected by the short term rental market; the jurisdiction issues may lead to all jurisdiction to have TSRs, although transaction costs might be high).

Sharing economy, gig economy, on-demand economy – looking for a definition

The sharing economy, gig economy or collaborative consumption became buzz words in the media in the last few years. These concepts are used to define businesses, non-profits or grassroots communities making shared use of underused resources, from material resources to skills. While most of the sharing economy enterprises use online platforms as the main network for exchange, there are offline examples. Some of these initiatives have already big corporations behind them and operate internationally, while others are very local. For example, Uber, Airbnb, BlaBlaCar, Upwork or Etsy are known worldwide, while initiatives like HelloCasa in France (for finding plumbers, electricians etc.) or variations of car sharing or bike sharing are serving local communities. Some of them charge users for the service they provide, others share for free. For example, while with Airbnb you pay a fee for sharing the apartment with a local, same service can be used for free for members of CouchSurfing, another sharing economy platform that allows people to access couches or beds in locals' homes for free. Thus, what we call generically the sharing economy is in fact a variety of models that are not always comparable in terms of processes, outcomes or general effects.

One of the first attempts to define the sharing economy or the collaborative consumption comes from Rachel Botsman (2010), the author of "What's Mine is Yours: How Collaborative Consumption is Changing the Way We Live". She defines the collaborative economy as "a system that activates the untapped value of all kinds of assets through models and marketplaces that enable greater efficiency and access." For Felländer et. al (2015) the sharing economy as "comprises the peer-to-peer exchange of tangible and intangible slack (or potential slack) resources, including information, in both global and local contexts. This mediated exchange tends to reduce transaction costs for users by replacing third-party intermediaries with digital platforms. However, the elimination of third-party intermediaries means that risks are often borne by the providers and consumers of resources rather than by a central actor." In their paper "Peer to peer Rental Markets in the Sharing Economy", Sundararajan and Fraiberger (2015) define the sharing economy as a broad array of "new platforms which facilitate market-based trade between private individuals for a variety of assets and services". Eckhardt and Bardhi (2015) state that sharing economy is not about sharing at all, but it is an access economy, defined by "convenient and cost efficient access to resources without the financial, emotional, or social burdens of ownership"; it is an economic exchange in which consumers look for utilitarian value, not social value.

Szoc (2015) states that while the terms defining these new business models have positive connotations (sharing economy, collaborative consumption), they hide practices that are far from this semantic. He proposes three criteria useful in distinguishing between true sharing and what some other authors call “platform capitalism”: (1) the monetization of the service; (2) the ownership of an asset in order to be able to provide the service and (3) the location factor. The common ground of all these services and goods is the matching between supply and demand through the means of an app or platform that allows individuals to participate in these markets; the prices these platforms offer are much lower than their traditional counterparts – as they don’t have agency costs (no investment in capital is needed from the platform, as users have their own capital to share, and, in many cases, social benefits and taxes are not paid either). In this new market, the platforms themselves establish the rules.

For Shor (2015), the sharing economy is simply peer-to-peer transactions facilitated by digital platforms. For Walker (2015), the common denominators of what we call the sharing economy are decentralized networks. Lee (2015) sees the sharing economy as “creative marketing” selling anti-establishment ideas. Parigi and Cook (2015) talk about the community-based organizations springing up the sharing economy. Richter et al. (2015) put the ICT at the core of the sharing economy but limit it to sharing of digital content, physical goods and crowdfunding. Aggregating the analyses of the above authors on what is sharing economy, we can identify the following critical dimensions to be used when defining the sharing economy and creating typologies:

- the type of assets - underutilized assets, idle capacity – both goods and services.
- the nature of the market: peer to peer or business to customer; market-based trade between private individuals; decentralized exchange - Peer-to-peer (P2P), Business-to-Consumer (B2C), Business-to-Business (B2B).
- reduced transaction costs for users by replacing third-party intermediaries with digital platforms; disruptive technology; sharing the knowledge of goods and services to better exchange them
- for profit vs. non profit.
- mechanisms of self-governance, horizontal networks and participation of a community.
- Offline or online service delivery.

When narrowing down this definition elements for Airbnb, we can conclude it is an ownership sharing business, with monetary incentives for the service provider (host) and it entails the sharing of physical assets – the space to be rented and the service is location-based, offline.

2. Empirical evidence on on-demand economy effects

There is little empirical evidence on how platform economy affects labour markets. In this chapter, I will summarize the main empirical findings in the field and explain how they help in assessing the impact of the sharing economy on labour.

Krueger and Hall (2015), in a first empirical study on Uber drivers in the US (using both survey and administrative data from Uber), show that Uber drivers are partnering with Uber mainly because the nature of the work, the flexibility and the compensation. By comparing Uber drivers with traditional taxi drivers they discover that Uber drivers are usually younger, there are more female drivers than in the traditional taxi companies, there are more white people driving for Uber than for traditional taxi companies and the Uber drivers are more educated (48% have at least college degree). In terms of employment status, there are three groups of Uber drivers: those who have no other job besides Uber (38%), driver-partners who work full-time on another job and partner with Uber (31%), and driver-partners who have a part-time job apart from Uber and partner with Uber (30%). When it comes to income, for 24% of the drivers Uber is their only source of personal income, for 16% Uber is their largest but not only source of income and for 38% Uber is a supplement to their income but not a significant source. In terms of wages the median hourly wage of an Uber driver is over 15$/hour, which is over the federal minimum wage of 7.25 and higher than hourly wages in the taxi industry. However, the hourly wage does not account for the fact that the drivers have to pay for gas, insurance, car usage, taxes, pension, healthcare or any other expenses the driver has. Also, we do not know if an hour of work includes the idle time between two rides or just the time spent on the ride is calculated. This research is relevant for the present papers as it shows how the sharing economy relates to labour and how employment transforms within such business models, from contract employment that pays benefits, car insurance and maintenance and so on to work in which all the responsibilities are transferred to the employee.

A JPMorgan Chase Institute (2016) study on how on-demand economy and platforms affect income volatility shows that from 2012 to 2015, the number of adults earning money from online platforms increased 47 times. The research looks at the 260 000 checking accounts with Chase bank in the US that had at least one online platform transaction in the last three years. They differentiate between ‘labour platforms’ (marketplaces for tasks and service delivery) and ‘capital platforms’ (marketplaces for rental or selling of goods). According to the report, the labour platforms tend to be used by younger, lower-income, rather male form Western US states individuals. Moreover, data shows that in the case of the labour platforms participants, the money earned through the platforms tend to replace other sources of non-platform income, while for the capital platforms users, the platform income is rather a supplement to their initial income. Within the labour platform participants, in September 2015, 25% of them earned 75% of their income through platforms and 46% of them relied on platforms for more than 25% of their income. On the capital platforms side, in September 2015, only 25% of active users relied on platforms for more than 25% of their income. This study helps make an argument that platforms like Airbnb, on which individuals who have spare rooms earn extra money, are rather used to supplement income, thus not replacing or creating jobs. In the line of the present paper, this is an important argument when it comes to stating that workers in the hotel industry may be affected by the presence of Airbnb.

In a research on the effects of Airbnb on the hotel industry in Texas, Zervas et. al (2016) show that in Austin, a place with high Airbnb availability, the effect on the hotel revenue is in the 8-10% range, affecting mostly lower-price hotels and hostels. The overall effect was that hotels responded to the presence of Airbnb through less aggressive pricing and, in the end, the sharing economy does take part of the traditional industries by providing "a viable, but imperfect, alternative for certain traditional types of overnight accommodation" (Zervas et all, 2016, p. 30). Their study is one of the first to assess the impact of the sharing economy on traditional businesses and their findings show that sharing economy businesses are changing patterns of consumption and becoming part of mainstream economic landscape they do not only appeal to niche markets, but impact the entire economy. One of their conclusions, related to how Botsman (2010) defines the sharing economy and how it relates to social welfare, states that indeed Airbnb is beneficial, not only to tourists that use Airbnb and to hosts earning extra money, but also to the tourists using traditional hotels and enjoy smaller prices (Zervas et all, 2016, p. 33). In this paper, I am looking at the other side of the coin, namely how these impacts Airbnb has on hotels affect the workers in the sector.

On the same topic of Airbnb, but on a completely different theoretical approach, Edelman and Luca (2014) show that white hosts on Airbnb in the US charge more than black hosts for similar listings, making a case for digital discrimination on peer-to-peer markets, if there is enough information about your service providing peer (photos, names that indicate race). In regard to welfare effects of the sharing economy, looking at peer to peer car rental markets, Sundararajan and Fraiberger (2015) find that sharing economy marketplaces significantly improve consumer welfare, and there are significantly higher improvements for the below-median income segment. Moreover, such markets impact ownership.

Quattrone et al. (2016) look at Airbnb effects in London from 2012 to 2015. They find that the properties listed on Airbnb are in well-to-do and attractive areas, where younger, more tech-savvy people live. The further from the centre, the less listings can be found. They also look at rooms versus entire homes differences and discover that rooms are listed rather in areas with highly-educated non-UK born renters, while entire apartments are listed in areas with more owners of high-end homes in terms of house price. The authors find that initially, in 2012, geographical distance from the centre was the most important predictor of the Airbnb penetration. The hosts were young and living in ethnically diverse and central neighbourhoods; there was a negative correlation with employment (authors suggest that early adopters may have been students). From 2013 to 2015 the geography becomes a less strong predictor; the correlations with income and owned properties become negative year after year and the authors conclude that late adopters are in need of extra income and they do not own their houses.

In terms of policy recommendations, Quattrone et al. (2016) propose Miller's 'transferable sharing rights' framework (Miller, 2014) in which prices are set by market demand and municipal policies (that could go even at neighbourhood level, depending on how a certain neighbourhood is affected). They say four factors matter when deciding on how to offer the sharing rights (number of permits): future consequences, impact on local economies, tourism sustainability and avoidance of agglomerations of short term rentals. The policies should be different for rooms and entire apartments and municipalities should incentivize data sharing, on which they should base their monitoring and further policy developments (Quattrone et al., 2016).

While media articles and analyses make a case on how Airbnb impacts local labour markets, there is, until now, no empirical study looking into changes in labour market structure, occupation structure or wage effects of Airbnb. Some empirical data and indications of such effects are made public by the traditional hotel industry associations and Airbnb, but, as they are merely lobby instruments, they should be treated with caution. Also, most of such evidence is available for US cities and less for Europe in general or Germany in particular.

An impact analysis report of HVS Consulting & Valuation (2015), "Airbnb and Impacts on the New York City Lodging Market and Economy", prepared for the hotel industry, provides insights on how loss in lodging industry due to Airbnb presence impacts the overall economy. According to the report, in one year, from September 2014 to August 2015, the hotel industry in NYC had 451 million dollars direct loss (5% of the hotel market) – which was calculated by simply collecting data on Airbnb revenues from Airdna (a data collection company dealing with Airbnb data) and further assumed that all guests that used Airbnb that year would have otherwise used a traditional lodging company. Based on this assumption, the report then estimates indirect losses for the hotel industry –

food, parking, extra hotel services, including effects on labour. The authors of the report claim that the 451$ loss in revenue equals about 2800 jobs in the hotel sector, and direct loss in labour income of 204 million $ (p.23). Additionally, there will be indirect job loss in sectors connected to the hotel industry. Further, there will be relevant impacts on construction industry and on taxes revenue, as the report states.

The European association for hotels, restaurants and cafes Hotrec (2015) released a policy brief in which they bring evidence on why the short-term rentals should be regulated Europe-wide, including employment reasons.

An analysis on Nasdaq webpage claims that while indeed Airbnb is a disruption for the hotel industry, it is likely that the financial performance of the hotel industry has to do more with difficult year-by-year comparisons and the assumptions about the microeconomic climate which would result in slower growth rates (Chilton REIT Team, 2015).

Another indication of the fact that Airbnb indeed affects labour market is the fact that there were negotiations between the company and a US labour Union, Service Employees International Union (SEIU) to reach a deal under which the company would promote employment of housekeeping personnel for their business with a 15$/hour wage (The Guardian, April 2016[1]). In the end, the SEIU union decided to back up a hotel workers' union which generally oppose Airbnb due to effects housing availability.

At the same time, Airbnb constantly publishes reports on its positive impacts on the local communities. The report for Berlin (which starting with May1st drastically regulated the business) shows that over 240000 tourists stayed with Airbnb in Berlin in 2015, generating 31,5 millions Euros for the hosts in berlin, of which 48% are spent for household costs, thus supporting the idea that Airbnb helps hosts keep their homes. They also claim 136,5 million Euros spending of guests in Berlin, out of which 45% is spent in the neighbourhood where the guest stays, thus contributing to the local economy[2].

---

[1] "Airbnb negotiations with powerful US labor union facing backlash ": https://www.theguardian.com/technology/2016/apr/18/airbnb-seiu-backlash-labor-union-deal-new-york-california and "Airbnb's controversial deal with labor union falls apart after intense backlash": https://www.theguardian.com/technology/2016/apr/21/airbnb-seiu-labor-union-deal-called-off-after-criticism

[2] Airbnb Belin – economic impacts infographic, available at: https://www.airbnb.de/berlin-economic-impact

3. Project description and methodological remarks

Study Problem

As seen above, there is strong evidence that digitalization will impact the labour market in various ways, either by creating new jobs, shifting some others, replacing or destroying some jobs. The evidence from the literature on on-demand economy effects on labour markets is less compelling, but reactions of the hotel industry representatives and Airbnb trying to make deals with labour unions indicate that there may be effects. As Zervas et. al (2016) show, high Airbnb availability has effects on hotel revenue and those effects are mostly felt by low-price hotels and hostels. This is enough evidence to support hypotheses related to similar effects on the labour market, once the hotel industry faces revenue loss. At the same time, Airbnb continuously reports how their business help hosts make ends meet and how Airbnb guests contribute to local economies (Airbnb Economic Impact, 2014). The Economic Impact report of the company looks into economic effects in several cities in US and Europe, using booking data, hosts and guests surveys and local economic research. The findings for Berlin for 2012 and 2013 show that Airbnb's total input into the local economy was around 100 Million euros. The company claims that Airbnb apartments are outside the hotel area of Berlin, thus "the average visitor spends € 311.85 (approximately $409) in the neighbourhood where they stay". Assuming that there is a link between local jobs and the fact that tourism becomes more spread within a city due to the Airbnb alternative, alternative hypotheses can be related to the fact that Airbnb has positive effects on other sectors, like restaurants, coffee shops, bakeries etc. The study problem is related to the effect on Airbnb on the employment in the hotel industry, operationalized in three different ways, which lead us to 3 research questions:
Does a higher Airbnb penetration rates correlate with less employees in the hotel industry?
Does a higher Airbnb penetration rates correlate with less full time employees in the hotel industry?
Does a higher Airbnb penetration rates correlate with smaller daily wages in the hotel industry?

Rationale of the Project

The academic scholarship in regard to digitalization of labour is fairly new and thus, still much anchored into theoretical and ideological debates. This paper adds to the underdeveloped empirical analysis literature, bringing data into the debate. The paper is among the first in the field that deals with the effects of Airbnb on the employment in the hotel industry. The results of the thesis should inform policy makers on how the structures of local labour markets are changing due to the presence of platform economy and easiness of outing underutilized assets to work. It will also give some inputs on the policy side so that negative effects could be outbalanced by policies. On the academic side, the research will add to the ongoing debate on how digitalization will affect jobs and if it will lead to job creation, job change, job destruction or job shifting.

The research question the thesis project aims to answer to is 'What are the effects of the on-demand economy on local labour markets in Germany?'. However, as data and previous empirical evidence are limited, we look at the same question through a sectoral perspective. Thus, we will assess the impact of Airbnb penetration on the hotel and accommodation sector. More precisely, I look at how the number of employees, the type of employment and the daily wage modifies in two groups of cities in Germany: a treatment group where Airbnb presence is high and a control group in which Airbnb presence is moderate.

The purpose of this study is to estimate effects of the on-demand economy on city-level labour markets, in the hotel industry. The following hypotheses will be tested:

H1: A higher Airbnb penetration rates correlate with less employees in the hotel industry

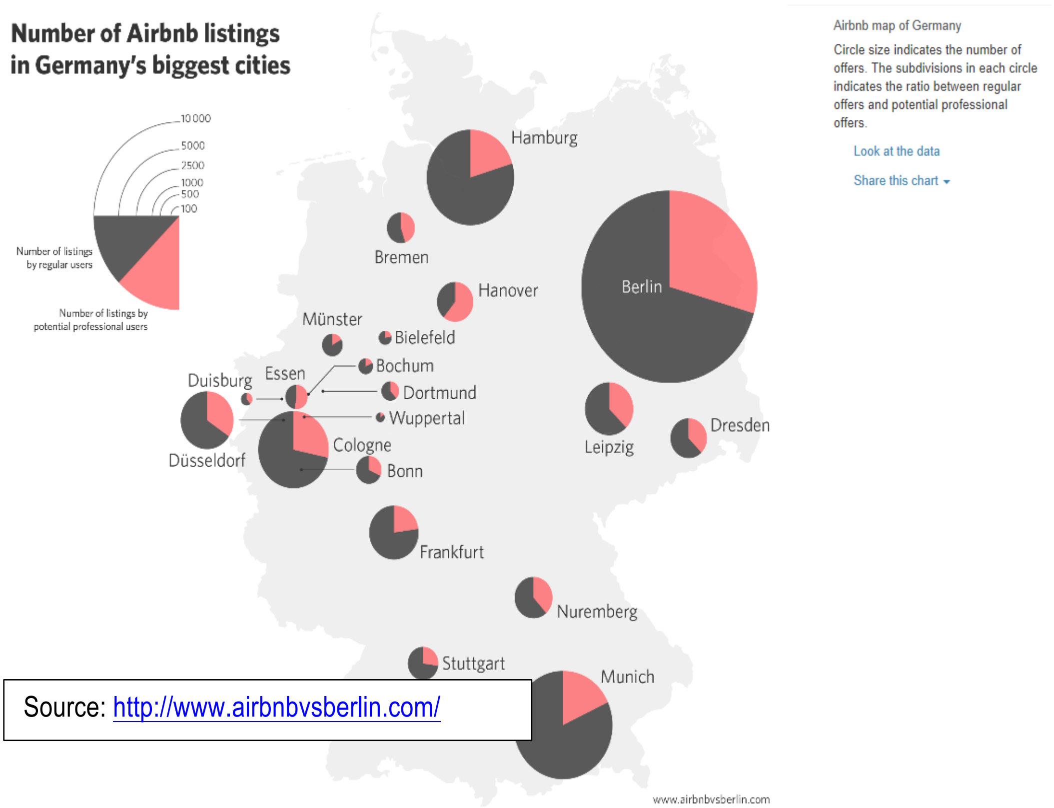
H2: A higher Airbnb penetration rates correlate with less full time employees in the hotel industry

H3: A higher Airbnb penetration rates correlate with smaller daily wages in the hotel industry

Methodology

Case selection and data collection

Figure 1. Airbnb penetration rates in Germany



Source: http://www.airbnbvsberlin.com/

The unit of analysis is urban level in Germany. As data on Airbnb listings is not available, I selected the 20 cities for which these data were made available by a German website, airbnbvsberlin. All other sources were rather limited, offering data for much less cities. . Some of the cities with high Airbnb availability are cities for which Airdna, a data company strictly working on Airbnb, reports are available. For each of these cities we know the number of Airbnb listings, measured in "active listings", ranging from around 1200 (in Frankfurt, Dusseldorf), to 2500 (Cologne), to around 3300 (Munich, Hamburg) to more than 12000 in Berlin. Other data sources are InsideAirbnb[3], according to which there are over 15000 listings in Berlin and Tom Slee's website which has data on Berlin (with 14922 listings), Bremen (574 listings) and Hamburg (over 4000 listings, as compared to 3256 active listings on Airdna)[4]. An anti-Airbnb campaign in Berlin, Airbnb vs. Berlin, also provides some comparative numbers in terms of listings. According to their research, Berlin has 11700 listings, while Munich has 4233, Hamburg 2921, Cologne 2997 and Frankfurt 1508.

[3] http://insideairbnb.com/
[4] http://tomslee.net/airbnb-data

It is worth mentioning that all of these sources webscrap the Airbnb website, thus there may be inconsistencies when it comes to the exact number of listings. However, they can be treated as proxies in relation to the Airbnb penetration rate in a certain place. In order for the Airbnb data on cities to be coherent and homogenous, I selected only one source, namely airbnbvsberlin[5], given that they mined data for the biggest 20 cities in Germany, as shown in the graph above. Thus, we look at 20 German cities from 2010 until 2014, with year 2012 being the baseline year for Airbnb starting its presence in Germany (when they acquired Accoleo, a similar German company). The 20 cities are: Berlin, Hamburg, Munich, Cologne, Frankfurt, Stuttgart, Düsseldorf, Dortmund, Essen, Bremen, Leipzig, Nuremberg, Dresden, Hannover, Duisburg, Bochum, Wuppertal, Bielefeld, Bonn and Münster.

Hypothesis testing

In order to identify sectoral effects of Airbnb on employment, I will use different approaches for each hypothesis to be tested.

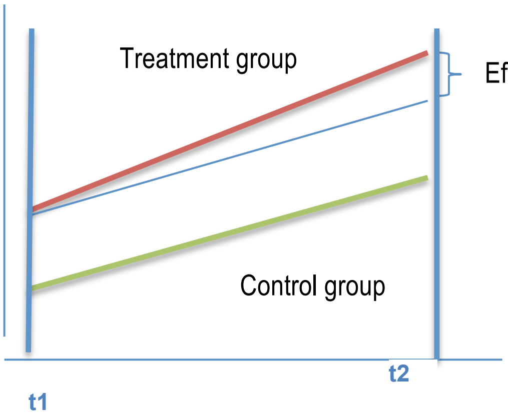
The first hypothesis, regarding employment in the hotel industry, will be tested by using descriptive statistics and OLS regression with hotel employment per city as dependent variable and Airbnb penetration score as the main predictor, then adding control variables for robustness checks. For the hypothesis regarding employment type, I use Probit regression, where full-time employment is computed as 1 and the other types of employments as 0.

For the daily wage variation, I will use a difference-in-differences strategy, where the outcome variable is the daily wage of a person employed in the hotel industry in a given city, at a given time. The treatment is the availability of Airbnb renting and the two groups will consist of the cities selected before (cities with high and low Airbnb penetration rate). As expected, Airbnb entered local markets at different speeds and with different intensities. Thus, the sample cities are divided in 2 groups, depending on how many Airbnb listings are available– considering some cities received the treatment and some did not. The control group will not be completely unaffected by the treatment – as the platform economy treatment is not randomly assigned to cities, thus we will have to control for external factors that may have impacted employment variables in different ways (recession impact – increases in unemployment, economic growth/stagnation, population, tourism indicators etc.). The two points in time for which the hypothesis will be tested against are 2010 (before Airbnb) and 2014

[5] http://www.airbnbvsberlin.com/

(post-Airbnb). The baseline year for Airbnb in Europe is 2012 (Airbnb bought the German competitor Accoleo in 2011, opening their first office in Europe in Hamburg) and the year to check for the effect will be 2014, but additionally we can check the effects over 3 to 4 years, depending on the available data.

Figure 2 DiD modeling



The treatment group (red line) is the group of cities receiving the treatment, thus we look at employment evolution in cities with high Airbnb offer The green line shows employment trends in cities with limited Airbnb offer. The assumption is that the two groups would have maintained their tendencies over time, if the treatment or other factors wouldn't have induced change. There were differences in wages patterns before the treatment and there will be some after the treatment, however, the difference between the differences will give us an estimate of how much the treatment affected the treatment group.

The relations between the four points in time and the differences are introduced in the regression equation bellow:

$$W_{it} = \beta_0 + \beta_1 D_{i,t} + \delta t + \gamma D_{i,1} + \varepsilon_{i,t}$$

W_{it} is the is the daily wage of individual i at time t, β_0 is the constant for all observations, $D_{i,t}$ is a dummy variable taking the value 1 if the individual is in the treatment group city and 0 if in the control group city, t is the time variable coded 1 if the individual is in the second time point and 0 for the first time point, $D_{i,1}$ is another dummy coded 1 only if the individual is in both the treatment group and the second time point and $\varepsilon_{i,t}$ is an error term. The coefficients of interest are β_1 – the constant for the treatment group; δ – the time effect and γ – the actual effect of the treatment for the treatment group. Given that additional factors may arise from the theoretical and legal analysis, the above equation will be extended to control for further predictors, adding up to a total of 6 models:

The first model is the classic difference in difference model, with log of daily wage as outcome variable:

$$\log (W_{it}) = \beta_0 + \beta_1 D_{i,t} + \delta t + \gamma D_{i,1} + \varepsilon_i \quad (1)$$

In order to check the robustness of the above model, we need to control several external predictors of daily wage in the hotel industry. Obviously, the Airbnb penetration score and the time effect are not the factors that will explain entirely the variation of wages in the hotel industry. It is rather likely that such factors only have a very small effect on wages in the hotel industry, which may rather depend on sector specific factors (how much tourism a city has, how big it is, how well connected to airports, train stations etc.) and on classic explanatory variables for wages (education, experience, gender etc.). Thus, the first two factors included in the model are city level population (yearly values) and nights spent in tourism accommodation facilities per city in a given year. The first control variable – population – is a proxy for city size, which may contribute to difference in wages. The second factor, nights spent in tourism accommodation facilities, is a proxy for the size of the hotel industry in a given city, which can also affect wages, as the better the industry is doing in a city, the more likely it is for wages to be bigger. Then I add city level unemployment and individual employment type as factors that contribute to differences in wages from city to city. Unemployment usually correlates with smaller wages, as the supply of labour is higher and the demand is low, while the individual type of employment distinguishes between full-time employment, part time employment, marginal part time employment or traineeships and internships, which also have an effect on how much a person earns. Then two classic perdictors for wage are added, education level and age as an approximation for experience. In looking at other factors could affect wages, I also controlled for the establishment size variable, considering that the number of employees is relevant to both how big a firm is and how much profit it makes, thus affecting wages. The last control variable added is gender, as the gender pay gap may also affect wages in the hotel industry.

$$\log (Dw_{it}) = \beta_0 + \beta_1 D_{i,t} + \delta t + \gamma D_{i,1} + Pop_t + Ns_t + \varepsilon_i \quad (2)$$

$$\log (Dw_{it}) = \beta_0 + \beta_1 D_{i,t} + \delta t + \gamma D_{i,1} + Pop_t + Ns_t + U_t + E_{i,t} + \varepsilon_i \quad (3)$$

$$\log(Dw_{it}) = \beta_0 + \beta_1 D_{i,t} + \delta t + \gamma D_{i,1} + Pop_t + Ns_t + U_t + E_{i,t} + Ed_{i,t} + A_{i,t} + \varepsilon_i \quad (4)$$

$$\log(Dwit) = \beta_0 + \beta_1 D_{i,t} + \delta t + \gamma D_{i,1} + Pop_t + Ns_t + U_{i,t} + E_{i,t} + Ed_{i,t} + A_{i,t} + Es_{i,t} + \varepsilon_i \quad (5)$$

$$\log(Dwit) = \beta_0 + \beta_1 D_{i,t} + \delta t + \gamma D_{i,1} + Pop_{i,t} + Ns_{i,t} + U_{i,t} + E_{i,t} + Ed_{i,t} + A_{i,t} + Es_{i,t} + G_{i,t} + \varepsilon_i \quad (6)$$

Treatment and control groups

In order to establish which of our 20 cities received the Airbnb treatment, we first look at the number of Airbnb listings in each city. In order to weight in the population factor, which is a proxy for how developed the city is, we then compute an Airbnb penetration score, namely the number of listings/100 000 population. The table below shows two possible treatment group assignments. The first one is purely mathematical and it splits the population into two equal groups, the first ten cities with the highest Airbnb penetration score being considered to have received the Airbnb treatment and the other ten not. The second selection splits the population in two groups based on a 140 Airbnb offers/100.000 population threshold, which takes into the treatment group only 6 cities, but the ones that stand out as outliers in terms of Airbnb offers.. The two treatment and control groups will be both used when applying the diff in diff procedure.

Figure 3 Treatment and control groups assignments

CITIES	Population 2014 (source: Eurostat)	District number	No. of Airbnb listings, Feb 2015 (Source: airbnbvsberlin .com)	**Airbnb Penetration score (listings/100000 population)**	Treatment vs. control I	Treatme vs. control I
Berlin	3.421.829	11.000	10479	306,24	1	1
Hamburg	1.746.342	2.000	2583	147,91	1	1
Munich	1.407.836	9.162	3316	235,54	1	1
Cologne	1.034.175	5.315	1681	162,55	1	1
Frankfurt	701.350	6.412	821	117,06	1	0
Stuttgart	604.297	8.111	312	51,63	0	0
Dusseldorf	598.686	5.111	945	157,85	1	1
Dortmund	575.944	5.913	105	18,23	0	0
Essen	569.884	5.113	167	29,3	0	0
Bremen	548.547	4.011	264	48,13	0	0
Leipzig	531.562	14.713	790	148,62	1	1
Dresden	530.754	14.612	447	84,22	1	0
Hannover	518.386	3.241	446	86,04	1	0

Nuremberg	498.876	9.564	484	97,02	1	0
Duisburg	486.855	5.112	44	9,04	0	0
Bochum	361.734	5.911	71	19,63	0	0
Wuppertal	343.488	5.214	26	7,57	0	0
Bielefeld	328.864	5.711	55	16,72	0	0
Bonn	311.287	5.314	219	70,35	0	0
Munster	299.708	5.515	143	47,71	0	0

4. Empirical analysis

Data description

The empirical data analysed in this research paper is a sample data of BeH database (Employee History) from IAB, which comprises of employment notifications with details about remuneration. For each individual, data includes demographic data (e.g. gender, age, education, place of residence) and employment history data (e.g. starting date, ending date, gross wages, establishment identification number, occupational status, current occupation). In BeH these data are linked with other establishment variables, such as location of establishment and branch of industry, which are drawn from the business data of the Federal Employment Agency (BA). BeH only covers workers covered by social security and marginal part time employees (Data products of the IAB Catalogue, 2012).

The sample used in this paper covers 2010-2014 period. The datasets were cleaned so that they cover only people employed in the hotel industry, people that are employees, marginal part-time workers and trainees. After establishing the 20 cities in the treatment and control groups, we subset the databases only for these 20 cities. In order to check for employment numbers, we then further aggregate the data for city levels, for the cities in the treatment and control groups. For the first hypothesis, I also look at employment variations between 2000 to 2014, in order to establish more longer-term patterns.

The data for Airbnb listings is taken from www.airbnbvsberlin.com, namely the number of available Airbnb apartments in each of the 20 cities. In order to compute the Airbnb penetration score we use Eurostat data on cities (Eurostat Urban Audit data[6]). Other independent variables used in the empirical analysis are unemployment data by cities in Germany and hotel beds/1000 population, extracted from the Federal Institute for Building, Urban Affairs and Spatial Development[7].

The Airbnb penetration score was calculated by the following formula:

Airbnb Penetration score = Airbnb listings*100000/population

In order to perform a DiD procedure, we added a dummy variable, post 2012, which takes 0 if the years are 2010, 2011, 2012 and 1 otherwise. The 2012 being the year Airbnb bought Accoleo, a similar home-sharing company operating locally in Germany, it will be consider the year in which the

[6] Eurostat Urban Audit data: http://ec.europa.eu/eurostat/web/cities/data/database last accessed on May 30th 2016.
[7] http://inkar.de/ last accessed on May 30th 2016

Airbnb "treatment" started to be administered, but the effects should be considered after 2012. The role of this variable is to assess the time effect pre and post Airbnb intervention.

The treatment variable is 0 if the penetration score is lower than 80 and 1 if higher - the 80 value was selected so that it splits the cities in two equal groups. The other split formula for the treatment looks at the biggest penetration scores and the threshold is 140. Then for each of the treatment variables we add an intervention variable taking the value of post2012*treat (1 or 2), which tells us if the individual is at the same time in the treatment group and in the second time period (case in which it will take the value 1) or not.

The rest of the variables are BeH variables. The daily wage variables will be used as is and the employment type variable, as a categorical variable, is transformed into a numeric variable taking the following values: 3 for employees, 2 for marginal part-time workers and 1 for trainees.

Beh Data sample used here has 8,661,105 observations from 2010 to 2014. From these observations, we only looked at the ones from the hotel industry (according to the German classification of sectors) and restaurant industry. When filtering for hotel industry only, there are 1,599,064 observations left, and when filtering for the 20 cities in our case selection we have 321,907 observations between 2010 and 2014 (54,926 for 2010; 46,904 for 2011; 71,550 for 2012; 73,738 for 2013 and 747,89 for 2014). For the restaurant industry, we looked at 5,326,867 observations overall and when filtering for the 20 cities selected here we were left with 1,398,545 observations (for 2010 we had 232,572; 194,351 for 2011; 314,039 for 2012; 324,920 for 2013 and 332,663 for 2014).

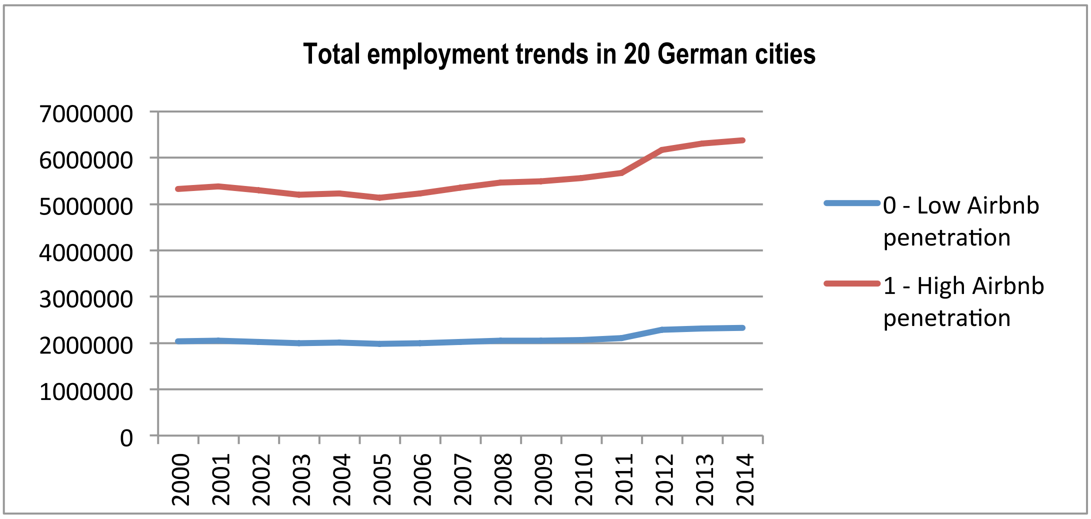
Airbnb and employment in the hotel industry

In this section of the paper we test the first hypothesis. As stated before, evidence so far leads to the idea that Airbnb presence should negatively affect the employment in hotels. As the hotel revenue goes down and the industry as a whole faces competition from Airbnb, it is likely that hotels would employ less people.

Considering the case selection strategy described above, we first need to check employment trends in general and in the hotel industry in particular for the selected cases, in order to assess potential changes that may occur due to Airbnb presence.

First, we look at all employment trends from 2000 to 2014, based on the two treatment and control group assignments described above. The graph bellow shows a general increase in total employment in all Germany (in absolute numbers), with a slightly higher slope for the cities with high Airbnb penetration scores. As these are also urban agglomerations, densely populated and economically developed, this is not a surprise.

Figure 4 Changes in employment, 2000-2014



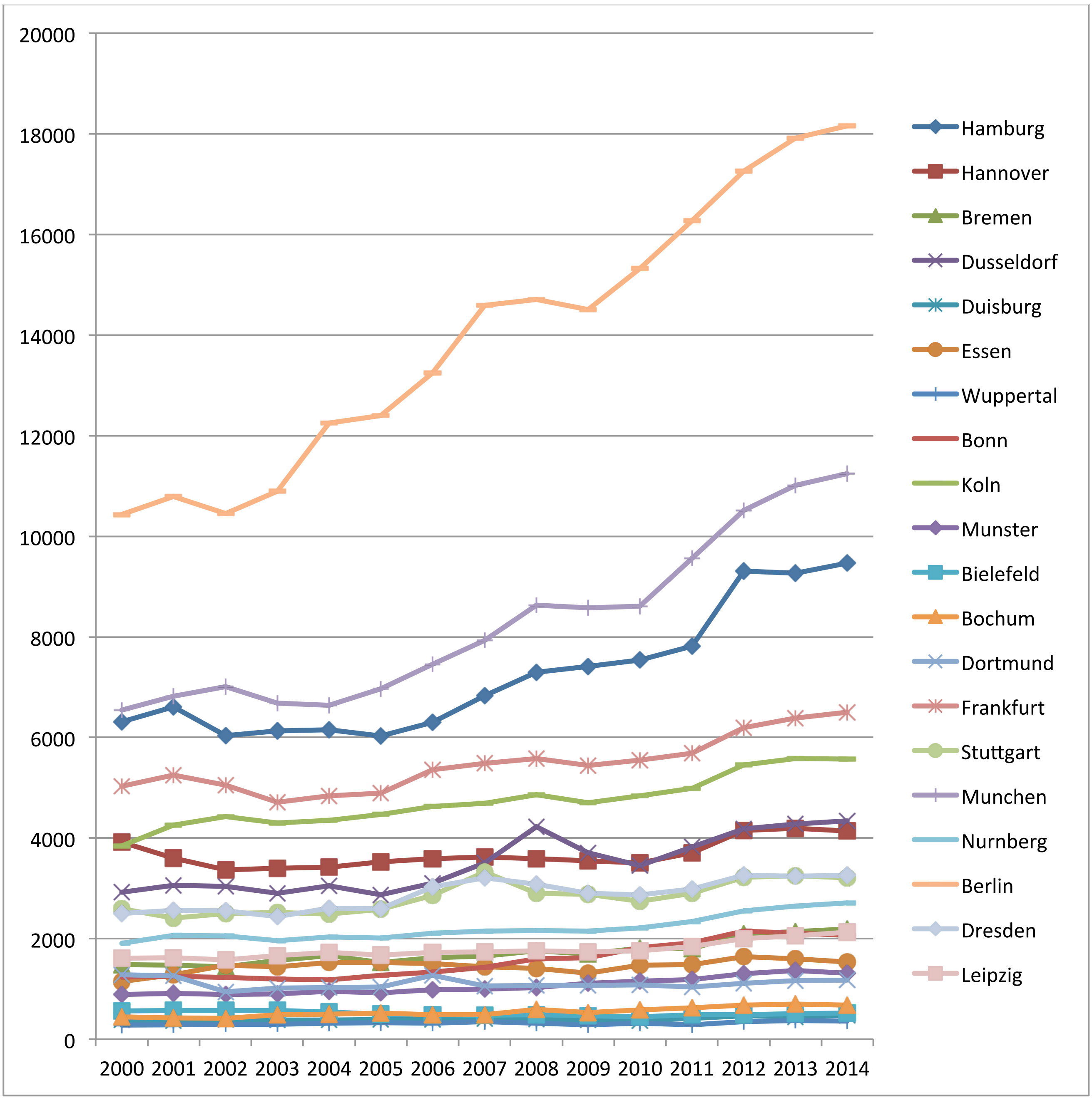
We can already see from the graph above the high Airbnb penetration scores correlate with more employment. As we talk about cities like Berlin, Munich, Hamburg or Koln, it is clear that a combination of tourism and business related causes leads to more employment in these cities, as Figure 4 shows.

However, if we look only at the employment in the hotel industry, the discrepancies between cities with high Airbnb penetration and the ones with low penetration are somewhat bigger. While they follow similar trends, with increases in hotel employment after 2006, those increases are much higher for the cities with higher Airbnb and visibly higher after 2012. As Figure 5 shows, the treatment and control groups used are at the threshold of 80 Airbnb penetration score. A city with more than 80 Airbnb offers per 100.000 inhabitants is considered to be a city with high Airbnb penetration. If indeed tourism or demand for short-term accommodation rentals increased in these particular cities, that may also be a reason for which owners of apartments or spare rooms hurried to post their spare spaces on websites like Airbnb. The fact that employment in the hotel industry increased more than general employment indicates that first, the demand was high and it is possible for Airbnb to have been a complementary service for the hotel sector, as a response to high demand.

Figure 5 Changes in hotel sector employment, 2000-2014

The first hypothesis states that once Airbnb is present in city, it affects the hotel employment. Thus, the first descriptive test of the first hypothesis is to look at how employment in the hotel industry changed between 2010 to 2014. The graph bellow shows changes in the number of people employed in the hotel industry for each individual city. As we can see, the trends in employment follow a similar trend, with 5 cities being outliers: Berlin, Munich, Hamburg, Frankfurt and Koln, which are also the cities with the highest population number.

Figure 6 Number of employees in the hotel industry for individual cities



However, if we look at the Airbnb penetration scores, the rankings are not similar, top cities in terms of Airbnb presence being Berlin, Munich, Koln, Dusseldorf and Leipzig, but closely followed by Hamburg. These 6 cities all have a penetration score higher than 140 Airbnb listings/100 000 population. Besides, the next ranked cities have much lower penetration scores, the next one being

Frankfurt, with 117 listings/100 000 population. The following table shows the changes in employment if we consider the cities split in 2 equal groups and increases in employment (absolute numbers) in each city. We then look at percentage increases in treatment and control groups.

Figure 7 Changes in hotel employment, 2010-2014

City	2010	2011	2012	2013	2014	Treatment	Increase
Bremen	1816	1802	2094	2142	2194	0	20,81
Duisburg	368	416	469	442	474	0	28,80
Essen	1468	1485	1645	1596	1539	0	4,84
Wuppertal	322	289	352	370	364	0	13,04
Bonn	1827	1917	2155	2110	2065	0	13,03
Munster	1152	1184	1300	1364	1312	0	13,89
Bielefeld	446	484	489	509	518	0	16,14
Bochum	587	624	676	697	683	0	16,35
Dortmund	1077	1037	1114	1165	1180	0	9,56
Stuttgart	2743	2901	3224	3255	3210	0	17,03
Control group	11806	12139	13518	13650	13539	0	14,68
Treatment group	55658	59026	64888	66588	67541	1	21,35
Pearson correlation coefficients, hotel employment and Airbnb penetration score: 2010: r=0.90 2011: r= 0.91 2012: r=0.90 2013: r= 0.91 2014: r=0.91							
Hamburg	7538	7811	9311	9261	9472	1	25,66
Hannover	3504	3702	4157	4190	4142	1	18,21
Dusseldorf	3455	3826	4182	4274	4342	1	25,67
Cologne	4843	4993	5451	5578	5569	1	14,99
Frankfurt	5546	5692	6195	6391	6502	1	17,24
Munich	8610	9560	10515	11017	11250	1	30,66
Nuremberg	2211	2342	2550	2652	2713	1	22,70
Berlin	15318	16274	17263	17921	18155	1	18,52
Dresden	2870	2982	3260	3246	3264	1	13,73
Leipzig	1763	1844	2004	2058	2132	1	20,93

The absolute numbers of employees in the hotel industry show that in cities with a higher Airbnb penetration score more people are employed in the hotel industry then in cities with lower Airbnb penetration score. The correlation coefficient between employment in the hotel industry and the Airbnb penetration score shows a strong positive correlation between the number of listings per 100 000 population and the number of people employed in the hotel industry each year. Thus, this is indication that the first hypothesis is not confirmed and a high presence of Airbnb may not lead to job loss in the hotel industry. Without any causal implications, the numbers show that the biggest cities have both a high Airbnb presence and more people employed in the hotel industry. As stated before, it may as well be the case that due to tourism levels in these cities, both Airbnb and hotels are increasing their business.

In order to check the correlation between employment in the hotel industry after the Airbnb emergence, we employ a linear regression in which hotel employment in 2014 is the dependent variable and the independent variables are the Airbnb Penetration score, the share of hotel employment of the total employment in 2011 (as in indicator for tourism size and considering that a shrinking or growing tourism market would affect employment some years later) and population. The results show a significant positive effect of Airbnb penetration score when considered alone and when considered in a model in which we control for the population factor, as shown in the next tables. However, once we introduce the share of employment in hotels from total employment, the Airbnb factor loses its significance. While not robust, the results do show that there is a positive relation between the number of Airbnb offers and the employment in the hotel industry.

Figure 8 OLS regressions - DI: employment in the hotel industry 2014

OLS regressions. Dependent variable –employment in the hotel industry 2014			
Hotel employment 2014 estimators			
	(1)	(2)	(3)
Airbnb	50.368***	23.256***	11.540
Pop $_{2014}$		0.004***	0.004***
ShareH $_{2011}$			2,612.397**
Observations	20	20	20
Adjusted R-squared:	0.824	0.948	0.959
*p<0.1; **p<0.05; ***p<0.01			

The following table shows changes in the share of hotel employment from total employment the in each city. As expected, the shares of hotel employment for the cities in the treatment group are slightly higher, potentially due to the number of hotels and touristic activity in these cities, in general. If we look at the changes between 2010 and 2014 in these shares, only two cities in the control group had less employment in hotels in 2014 compared to 2014, Essen and Munster. On average, employment in the hotel industry increased in both groups, slightly more in the treatment group, which reinforces the fact that the first hypothesis is false, namely, the presence of Airbnb did not affect the number of people employed in the hotel sector.

Figure 9 Share of hotel employment of total employment, 2010-2014

City	2010	2011	2012	2013	2014	Change 2010-2014	Treatment
Bielefeld	0,3	0,32	0,29	0,3	0,3	0	0
Bochum	0,41	0,43	0,43	0,44	0,44	0,03	0
Bonn	1,06	1,09	1,13	1,09	1,07	0,01	0
Bremen	0,67	0,65	0,69	0,69	0,71	0,04	0
Dusseldorf	0,88	0,95	0,97	0,98	0,99	0,11	0
Dresden	1,19	1,21	1,25	1,23	1,22	0,03	0
Essen	0,58	0,58 1	0,6	0,58	0,55	-0,03	0
Munster	0,72	0,72	0,72	0,74	0,7	-0,02	0
Stuttgart	0,74	0,77	0,77	0,76	0,74	0	0
Wuppertal	0,25	0,22	0,25	0,26	0,25	0	0
Control group average	0,68	0,69	0,71	0,71	0,70	**0,02**	0
Treatment group average	0,81	0,76	0,77	0,77	0,86	**0,05**	1
Berlin	1,24	1,29	1,27	1,28	1,29	0,05	1
Dortmund	0,45	0,43	0,42	0,44	0,45	0	1
Duisburg	0,2	0,23	0,24	0,23	0,25	0,05	1
Frankfurt	1,07	1,09	1,09	1,11	1,11	0,04	1
Hamburg	0,84	0,86	0,94	0,91	0,93	0,09	1
Hannover	0,72	0.74	0.77	0.76	0,74	0,02	1
Cologne	0,93	0,94	0,94	0,94	0,93	0	1
Leipzig	0,75	0,76	0,76	0,76	0,76	0,01	1
Munich	1,15	1,25	1,23	1,26	1,27	0,12	1
Nuremberg	0,76	0,79	0,79	0,81	0,83	0,07	1

In conclusion, in the two years since Airbnb started their business in Germany, employment in the hotel industry was not affected. By contrary, cities with more Airbnb offers have more people employed in the sector. This indicates that Airbnb offers may have simply responded to existing demand and supplemented hotel rooms, thus contributing to the local economy. While the results are not significant when we control for population and share of hotel employment from total employment, the Airbnb penetration score correlates with the number of employees in the hotel sector. The interpretation of these results should be made with caution: two years may be too short for assessing the effects of Airbnb on the number of employees in the hotel sector. Further research should monitor the changes in employment in order to grasp medium and long term effects. Moreover, analysing these data seasonally could give more insights on the effects, as the hotel industry is one prone to seasonal hiring.

The effect of Airbnb on employment structure in the hotel industry

In this section I verify if Airbnb presence correlates in any way with the employment structure. Looking at two groups of employees, full-time and other type, I employ a Probit regression in which the type of employment (a dummy variable taking the value 1 for full-time employees and 0 for other types of employment) is the dependent variable. The first model is a simple Probit regression between the type of employment and Airbnb penetration score. The type of employment in the individual value for the employees in the database and the penetration score is calculated as the number of Airbnb offers per 100.000 population, at city level:

$$E_{it} = \beta_0 + \beta_1 AirbnbPenetr + \varepsilon_i \quad (1)$$

In the next model I add control variables in regard to size of the city and the size of the hotel industry. The population is the absolute number of people living in a certain city and the size of the hotel industry is counted as number of nights spent in tourism accommodation facilities:

$$E_{it} = \beta_0 + \beta_1 AirbnbPenetr + Pop_t + Ns_{i,t} + \varepsilon_{i,} \quad (2)$$

In order to control for economic development in terms of labour markets, I add unemployment at city level as an independent variable in the model:

$$E_{it} = \beta_0 + \beta_1 AirbnbPenetr + Pop_{i,t} + Ns_{i,t} + U_t + \varepsilon_{i,} \quad (3)$$

The following model adds individual education and age as predictors for the type of employment, considering that it is likely that the higher the education level and the higher the age (as a proxy for experience), the higher the chances to be a full-time employee:

$$E_{it} = \beta_0 + \beta_1 AirbnbPenetr + Pop_{i,t} + Ns_{i,t} + U_{i,t} + Ed_{i,t} + A_{i,t} + \varepsilon_i \qquad (4)$$

The establishment size could also affect the type of employment:

$$E_{it} = \beta_0 + \beta_1 AirbnbPenetr + Pop_t + Ns_t + U_t + Ed_{i,t} + A_{i,t} + Es_t + \varepsilon_i \qquad (5)$$

The last control variable added is gender:

$$E_{it} = \beta_0 + \beta_1 AirbnbPenetr + Pop_{i,t} + Ns_{i,t} + U_{i,t} + Ed_{i,t} + A_{i,t} + Es_{i,t} + G_{i,t} + \varepsilon_{i,t} \qquad (6)$$

The following table summarizes the results of the Probit regressions with the models explained above.

Figure 10 Probit regressions. Outcome variable - type of employment hotels, 2010-2014

Probit regressions. Outcome variable –type of employment in hotel industry (Full-time employment – 1; others employment type - 0), 2010 - 2014						
Type of Employment estimators						
	(1)	(2)	(3)	(4)	(5)	(6)
AirbnbPenetr	**0.0005*** **	**0.0006*** **	**0.0006*** **	**0.0005*** **	**0.0005*** **	**0.0004*** **
$Pop_{i,t}$		-0.000***	-0.000*	0.000***	-0.000***	0.000***
$Ns_{i,t}$		0.000***	-0.000	-0.000***	0.000***	-0.000***
$U_{i,t}$			-0.005***	-0.000***	-0.001***	-0.001***
$Ed_{i,t}$				0.003***	0.003***	0.003***
$A_{i,t}$				0.002***	0.002***	-0.002***
$Es_{i,t}$					0.000	0.000
$G_{i,t}$						0.031***
Observations	280189	280189	214939	124749	124748	124747
Adjusted R-squared:	0.013	0.014	0.014	0.017	0.017	0.020
*p<0.1; **p<0.05; ***p<0.01						

Airbnb penetration scores have a positive effect on employment type, thus showing that in cities with a high Airbnb penetration, full-time employment is more frequent. The effect size is very small, but highly significant throughout the six tested models. The same tendencies in terms of significance are present when we look at population and the size of the hotel industry, although the results show both positive and negative effects when we add factors into the regression models. The explanation may be the fact that bigger cities, with more hotels, may tend to employ more people full-time, but also more seasonal workers and marginal part-time workers, thus the effects being unclear. City level unemployment has a steady negative impact on the type of employment, while education always has a positive effect. Age positively affects the probability of being full-time employed, but when we control for gender (counted as 1 if the employee is male), the effect is negative. That shows that older women are rather in other forms of employment than full-time. Establishment size does not seem to affect employment type, the results not being significant. As in the case of population and nights spent, the explanation may be that bigger companies have both more full-time and more other types of employment. When it comes to gender, the probability of being in full-time employment is 3% higher for male employees, all other variables being constant. In conclusion, in cities with more Airbnb, the probability of workers in the hotel industry being in full-time employment is higher than in the cities with less Airbnb offers. The limitations of this procedure stand in the fact that the time factor is not taken into account and it basically proves that in bigger cities it is likely to have more full-time employment in the hotel industry than in smaller ones.

In conclusion, the effects on employment types can be interpreted as mixed. While it is clear that more Airbnb is correlated with more full-time employment, this is not a causal relationship. There can be multiple explanations for this fact: the cities with more Airbnb are also cities that are likely to have big chain hotels that hire more people full-time (thus population and share of hotel employment from total employment being strong predictors of the type of employment) and they are the cities in which tourism (either business of leisure tourism) plays an important role in the local economy.

The impact of Airbnb on average daily wages in the hotel industry

In this section I check the effect of Airbnb as treatment on the daily wage. The method used is difference in difference regression. Thus, daily wage is a function of the observation the data base being after 2012, exposure to treatment, and the subject being both in the treatment group and in the post-treatment period. I do this procedure using both assignments procedures, the first one splitting the 20 cities in 2 equal groups and considering the 10 with the highest Airbnb penetration scores as the treatment group and the others as control group, as shown above. The second treatment assignment procedure considers as affected by treatment only the 7 cities that are visibly outliers in terms of hotel employment and have an Airbnb penetration score of more than 140 offers/100.000 population.

First I do the difference in difference procedure manually, as shown in the following table. I look at average wages for all individuals employed in the hotel sector from 2010 to 2012 and then in 2013 and 2014. Both groups register increases in daily wages from 2010 to 2014, however, the increases in the cities with less Airbnb are with 24 eurocents higher, on average. This may seem counterintuitive, given previous results that show high correlation between the Airbnb treatment and both number of employees and the type of employment. If so far it seemed that in cities where Airbnb is more present, more people are employed in the hotel sector and more of those tend to be in full-time employment than in cities where Airbnb is less present. This trend changes when we look at daily wages. In this case, cities with less Airbnb have higher wage increases in the post treatment period. In line with the previous findings, the treatment group cities have much higher average daily wages and that does not change.

Figure 11 DiD table for daily wage means in the hotel industry, 2010-2014

	Treatment Group (penetration >80)	Control Group (penetration >= 80)	Difference
2010 - 2012	49.45	41.26	8.19
Post 2012	50.61	42.66	7.94
Change	1.16	1.40	**-0.24**

I then use regression analysis with the difference in difference estimators. The models used are similar to the ones used above, for the Probit regressions. The first equation is a classical difference in difference regression model. The outcome variable Dw_{it} is the daily wage of individual i at time t. $D_{i,t}$ is a dummy variable for the individual being in the treatment group (value 1) or the control group (0); t is the time variable, in this case taking the value of 0 if the data is between 2010 to 2012 and 1 for 2013 and 2014. $D_{i,1}$ is another dummy coded 1 only if the city is in both the treatment group and the second time point and $\varepsilon_{i,t}$ is an error term. The coefficients of interest are β_1 – the constant for the treatment group; δ – the time effect and γ – the actual effect of the treatment for the treatment group.

$$Dw_{it} = \beta_0 + \beta_1 D_{i,t} + \delta t + \gamma D_{i,1} + \varepsilon_{i,} \tag{1}$$

I then add the city level independent variables, population and total nights spent in tourism accommodation:

$$Dw_{it} = \beta_0 + \beta_1 D_{i,t} + \delta t + \gamma D_{i,1} + Pop_t + Ns_t + \varepsilon_{i,} \tag{2}$$

In the third model, we add unemployment as a control for economic growth on the labour market at city level and employment type (employee, marginal part-time worker and trainee) at individual level, as predictors for wage:

$$Dw_{it} = \beta_0 + \beta_1 D_{i,t} + \delta t + \gamma D_{i,1} + Pop_t + Ns_t + U_t + E_{i,t} + \varepsilon_{i,} \tag{3}$$

We also control for education and age as having an impact on daily wage. Education is coded in the following manner: "Primary school" – 1; "Primary school vocational"- 2; "Secondary school" – 3; "Secondary school vocational" – 4; "University degree" and "Applied university"- 5:

$$Dw_{it} = \beta_0 + \beta_1 D_{i,t} + \delta t + \gamma D_{i,1} + Pop_{i,t} + Ns_{i,t} + U_{i,t} + E_{i,t} + Ed_{i,t} + A_{i,t} + \varepsilon_{i,} \tag{4}$$

The next model controls for establishment size:

$$Dw_{it} = \beta_0 + \beta_1 D_{i,t} + \delta t + \gamma D_{i,1} + Pop_t + Ns_t + U_t + E_{i,t} + Ed_{i,t} + A_{i,t} + Es_{i,t} + \varepsilon_{i,} \tag{5}$$

In the last model, I add gender (1 if male, 0 if female)as a control variable affecting daily wages:

$$Dw_{it} = \beta_0 + \beta_1 D_{i,t} + \delta t + \gamma D_{i,1} + Pop_t + Ns_t + U_t + E_{i,t} + Ed_{i,t} + A_{i,t} + Es_{i,t} + G_{it} + \varepsilon_{i,} \tag{6}$$

The following table shows the results of the DiD regressions with the above equations. The first model shows that being in the treatment group and in the second time period negatively impacts the daily wage ($D_{i,1}$ ($t^* D_{i,t}$)). While the coefficient is not significant when only DiD estimators are factors in the regression, once control variables are added, they become significant at 0.01 level. When controlling for population and tourism size, the results show that workers in the hotel industry in the cities with more Airbnb and after 2012 earn 3,3 euros less per day then workers in the same sector in cities that have less Airbnb presence. As factors are added in the regression, the values decrease. At the same time, the adjusted R-squared values increase when we added the individual factors that impact wages (employment type, education, age, gender). The factors that have the biggest effect on wages are the employment type, education and gender. The time effect is positive and significant (wages increase with time), but after controlling for education and age they become negative and insignificant. The treatment estimator (being in a city with more Airbnb) is always significant and positive and significant, which shows that cities with more Airbnb presence have, on average, higher wages in the hotel sector. Population has a negative impact on wages in the hotel industry on average. The tourism sector size has a positive on wages, the more nights spent in the touristic accommodations, the higher the salary. The estimates are very small due to the fact that both variables were uses in absolute values. Unemployment has a negative effect on wages and age a positive, but rather small one. The size of the company has a small and less significant positive effect on daily wages.

Figure 12 DiD regressions. Outcome variable - daily wage of workers in the hotel industry

Difference in difference regressions. Outcome variable – daily wage of workers in the hotel industry, 2010 - 2014						
Daily wage estimators						
	(1)	(2)	(3)	(4)	(5)	(6)
t	1.406***	1.048***	0.803***	-0.128	-0.152	-0.155
$D_{i,t}$	8.194***	6.661***	3.113***	1.463***	1.455***	1.257***
$D_{i,1}$ (t^* $D_{i,t}$)	**-0.245**	**-3.345*** **	**-2.409*** **	**-1.709*** **	**-1.719*** **	**-1.643*** **
$Pop_{i,t}$		-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
$Ns_{i,t}$		0.000***	0.000***	0.000***	0.000***	0.000***
$U_{i,t}$			-1.066***	-1.320***	-1.319***	-1.302***
$E_{i,t}$			27.511***	24.539***	24.538***	24.322***
$Ed_{i,t}$				3.172***	3.170***	3.423***
$A_{i,t}$				0.083***	0.083***	0.072***
$Es_{i,t}$					0.0001**	0.0001*
$G_{i,t}$						9.034***

Observations	319,447	319,447	245,192	149,291	149,291	149,291
Adjusted R-squared:	0.009	0.019	0.356	0.366	0.366	0.383
*p<0.1; **p<0.05; ***p<0.01						

The next table shows the regression results of the same models on log of daily wage. The significance and the effects size remains the same. The specific effect of being both in the treatment group and after 2012 on the daily wage varies between -2% and -7%.

Figure 13 DiD regressions. Outcome variable - log daily wage of workers in the hotel industry

Difference in difference regressions. Outcome variable – log daily wage of workers in the hotel industry, 2010 - 2014						
Log Daily wage estimators						
	(1)	(2)	(3)	(4)	(5)	(6)
t	0.030***	0.022***	0.014*	-0.008	-0.009	-0.009
$D_{i,t}$	0.250***	0.201***	0.110***	0.046***	0.046***	0.043***
$D_{i,1}$ ($t^* D_{i,t}$)	**-0.008**	**-0.075*** **	**-0.050*** **	**-0.025*** **	**-0.025*** **	**-0.024*** **
$Pop_{i,t}$		-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
$Ns_{i,t}$		0.000***	0.000***	0.000***	0.000***	0.000***
$U_{i,t}$			-0.027***	-0.025***	-0.025***	-0.025***
$E_{i,t}$			0.780***	0.687***	0.687***	0.684***
$Ed_{i,t}$				0.017***	0.017***	0.021***
$A_{i,t}$				-0.006***	-0.006***	-0.007***
$Es_{i,t}$					0.000***	0.000**
$G_{i,t}$						0.152***
Observations	319,447	319,447	245,192	149,291	149,291	149,291
Adjusted R-squared:	0.011	0.018	0.392	0.420	0.420	0.429
*p<0.1; **p<0.05; ***p<0.01						

In order to further check for robustness, the same models are applied for subgroups or with different treatment assignment procedures. First, if we only select the full-time employees and exclude the employment type from the models, the results are much stronger. Only by looking at difference between the control group and the treatment group in the two points in time, the differences in daily wages are now almost one euro, about five times higher than the difference on average daily wages for all hotel industry workers.

Figure 14 DiD table - daily wage of full-time workers in the hotel industry

	Treatment Group (penetration >80)	Control Group (penetration >= 80)	Difference
2010-2012	67.38	65.16	2.21
Post 2012	71.12	69.87	1.25
Change	3.74	4.70	**-0.96**

The regression results on full-time employees' daily wages follow the same trends as the ones on all hotel works, but are a little stronger. In absolute terms, the effect of the Airbnb intervention (when an employee is both in the treatment group and after 2012) account for between 96 eurocents and 4.3 euros a day, all statistically significant at 0.01, but in percentages, the proportions of 1% to 6% decreases of the daily wage are kept. The results can be seen in annexes 1 and 2.
Another robustness check consists of applying the same regressions to occupational subgroups. When we only look at cooks and waiters employed in the hotel industry (Annex 3 and 4), the effects remain between 1% to 6% daily wage decreases. They are less significant for all cooks (0,1) and highly significant for full-time cooks only (0,01). For the waiters (Annex 4), the trends are the same – a small negative effect, however, the results are not significant when control variables are added. This shows that the effect may vary depending on occupations and it leads to further research questions in this respect.
When the treatment assignment procedure is changed and only cities with over 140 Airbnb penetration scores are considered to have received the Airbnb treatment, the effects of Airbnb on daily wages are in the -1% to -4% range, significant at 0.01, as seen in the table below. The six cities with Airbnb penetration scores over 140 are Berlin, Hamburg, Munich, Cologne, Dusseldorf and Leipzig. The effects are less strong than for the more heterogeneous treatment and control groups with 10 cities each. The other four cities in the original treatment group were Frankfurt, Nuremberg, Hannover and Dresden. The results indicate the possibility that Airbnb presence affects wages in cities that are medium-sized and receive a moderate quantity of the treatment. Thus, further research could take into account three types of groups, one with high Airbnb presence, one with a medium presence and one with low or no Airbnb presence.

Figure 15 DiD regressions. Outcome variable - log daily wage of workers in hotels (Airbnb>140)

Difference in difference regressions. Outcome variable – log daily wage of workers in the hotel industry, 2010 – 2014, when the treatment group is made of cities with an Airbnb Penetration score > 140						
Log Daily wage estimators						
	(1)	(2)	(3)	(4)	(5)	(6)
t	0.021***	0.006	-0.005	-0.020***	-0.020***	-0.020***
$D_{i,t}$	0.147***	0.180***	0.086***	0.050***	0.050***	0.047***
$D_{i,1}$ ($t^* D_{i,t}$)	**0.012***	**-0.091*****	**-0.045*****	**-0.019*****	**-0.019*****	**-0.018****
$Pop_{i,t}$		-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
$Ns_{i,t}$		0.000***	0.000***	0.000***	0.000***	0.000***
$U_{i,t}$			-0.024***	-0.023***	-0.023***	-0.023***
$E_{i,t}$			0.781***	0.688***	0.688***	0.684***
$Ed_{i,t}$				0.017***	0.017***	0.021***
$A_{i,t}$				-0.006***	-0.006***	-0.007***
$Es_{i,t}$					0.000**	0.000**
$G_{i,t}$						2.252***
Observations	319,447	319,447	245,192	149,291	149,291	149,291
Adjusted R-squared:	0.007	0.018	0.392	0.420	0.420	0.429
*p<0.1; **p<0.05; ***p<0.01						

When we check the same effects by employing an OLS regression with log of daily wage of full-time employees as a dependent variable, the effect of Airbnb penetration score is positive and significant, although very small (see Annex 6), daily wages being higher with 0,1 to 0,2%. The insight provided by this test is that time effects are highly relevant when analysing the impact of Airbnb on hotel industry wages. As the time span of this research only covers two years of Airbnb presence in Germany and we see negative effects only when we control for the year effects, further research is needed in order to fully grasp such effects on longer term. What the OLS regression shows is that there is a correlation between the cities with high Airbnb penetration and wages and that correlation is positive. This indicates that indeed bigger cities with more tourism industry have higher wages in the hotel industry. Since the diff in diff approach shows a negative correlation, what we learn from employing the OLS regression is that time is highly relevant when it comes to assessing effects of Airbnb on hotel industry wages.

As Zervas et al. (2015) show that in Texas, US, most affected by Airbnb presence are hostels and small hotels, I looked at wage effects for small and medium enterprises in the hotel industry in Germany. Annex 7 shows the results of the difference in differences regressions for SMEs only. The negative and significant effect is maintained, but the effects are higher, daily wages being with 6% to 14% lower for the employees in the cities with high Airbnb presence and after 2012.

If I only look at two points in time, 2010 and 2014, not considering the averages for the 2010-2012 time period, respectively 2013-2014, the differences for all employees is higher for the cities with high Airbnb penetration scores (there is an increase in daily wages in these cities of 0.44 euros on average, as show in table 16), but as control variables are added, the estimators become negative (see Annex 8).

Figure 16 DiD Table - differences in daily wages in 2010 and 2014, hotel industry

	Treatment group	Control group	Diff
2010	49.32	41.79	7.52
2014	51.25	43.28	7.97
Diff	1.92	1.48	0.44

If only full-time employees are considered, the difference between daily wages in the control and treatment group are negative, namely the full-time employees in the treatment group have a daily wage with 1,39 euros less than the ones in the control group, on average. The DiD regression results indicate a somewhat stronger effect on full-time employees (see Annex 9).

Figure 17 DiD table - daily wages of full-time workers in the hotel industry, 2010 and 2014

	Treatment	Control	Diff
2010	65.08	62.39	2.68
2014	71.99	70.70	1.29
Diff	6.91	8.30	**-1.391976**

In order to check the effects on a similar industry that can be equally affected by Airbnb, I also look at wages in the restaurant industry in the same cities. The reasons for looking at the restaurant industry, as a robustness check for the effects on hotel industry is twofold: positive extrernalities as a consequence of Airbnb and the similarity of the two sectors. First, as Airbnb puts it, there may be a positive economic impact of Airbnb on cities, which helps local businesses and supports local jobs (Airbnb Economic Impact, 2014). The same source shows that, for example, in Paris, 27% of the Airbnb guests declare that they would not have visited Paris if it was not for Airbnb or that Airbnb guests spend more time and more money in the cities they visit in comparison with hotel guests. Considering that there is a positive economic spill over of Airbnb, the restaurant industry should be one of the industries benefiting of such spillovers, as the tourism is rising and the tourists spend more time and money in the cities. Thus, while for the hotel industry Airbnb can be competition, for the restaurant industry can mean more revenue, which, in return, can lead to higher salaries in the restaurant sector. Second, the hotel sector and the restaurant sector are similar in terms of employment (education levels, seasonality, tourism related etc.) and usually taken together by policy makers. Being similar in this sense and restaurants being sometimes part of hotels, there are reasons to believe some restaurants at least will be negatively affected. For example, being in an Airbnb home allows people to cook for themselves, thus they may not go to a restaurant as often as hotel guests. Given these two rather opposite possibilities, it is worth examining to what extent Airbnb affects also the workers in the restaurant industry and how the effects are compared to the wages in hotels.

When we look at all workers in the restaurant sector in the 20 cities in Germany between 2010-2012 and 2013-2014, the average difference show a higher increase in average daily wages for restaurant employees in the treatment group (Figure 18), thus indicating that Airbnb may positively affect restaurant revenues as part of their positive effects on local economies, as the company claims (Airbnb Economic Impact, 2014). Although the difference is small (9 eurocents on average more for the workers in cities with high Airbnb penetration), it is clearly a different situation from the hotel workers differences, which were negative for the workers in cities with more Airbnb offers. However, if only full-time employees in the restaurant industry are selected, the difference becomes negative (Figure 19), which tells us that rather full-time employees in restaurants are affected, just like in the case of hotels, where for full-time employees only, the differences are higher. The insight we get from looking at these two sectors in comparison is that first, if we look at overall employment, in cities with higher Airbnb penetration scores the wages in the hotel sector decrease on average from 2010-2012 to 2013-2014, while they increase for the restaurant sector in the same time periods. This means that overall, Airbnb correlates negatively with wages in the hotels and positively with wages in restaurants. For full time employees only, the correlations for both sectors are negative.

Figure 18 DiD table - daily wages in the restaurant industry, 2010-2014

	Treatment Group (penetration >80)	Control Group (penetration >= 80)	Difference
2010-2012	27.11	27.08	0.03
2013-2014	27.55	27.42	0.122
Difference	0.43	0.34	**0.09**

Figure 19 DiD table - daily wages in the restaurant industry, full-time employees only, 2010-2014

	Treatment Group (penetration >80)	Control Group (penetration >= 80)	Difference
2010-2012	52.58	51.45	1.13
2013-2014	58.86	58.00	0.86
Difference	6.27	6.54	**-0.2719985**

Annexes 10 and 11 show the DiD regression results for the restaurant industry, for all employees and for full-time only. Initially, the effect of being in a city with high Airbnb penetration score and after 2012 is negative and only significant for full-time workers. Once control variables population and the number of nights spent in tourism accommodation spaces were added, the estimators became positive. When the rest of the control variables were added, the coefficient became statistically insignificant and positive (with one exception – the last model in Annex 10). This shows that we cannot claim strong correlations between Airbnb presence in the post 2012 period in a city and wages in the restaurant industry. By comparison, the claim that decreasing wages in the hotel industry are correlated with more Airbnb offers after 2012 is valid.

Conclusions

Digitalization and the spread of technology brought innovations in industry and service delivery. By using Internet platforms in order to match supply with demand, the sharing economy opened the markets for new types of services, namely peer-to-peer services. In the last years, such services became mainstream, challenging traditional business models and disrupting industries. This paper adds to the empirical research on sharing economy, by looking at the way Airbnb affects hotel industry. It is one of the first papers linking data on Airbnb penetration rates with employment data from Germany, providing evidence on the impact of the sharing economy on labour markets.

I look into three employment variables in 20 cities in Germany. The cities are split into treatment and control groups, the treatment group consisting of cities in which there are more than 80 Airbnb offers per 100.000 inhabitants. The time periods checked are 2010-2012, period in which Airbnb was not present in Germany, and 2013-2014, after Airbnb penetrated the short term rental market in Germany. In terms of employment variables, I looked at the number of employees in the hotel sector at city level, the type of employment at individual level (full-time or otherwise) and individual daily wages.

The analysis shows that in the 2012 - 2014 period, the employment in the hotel sector increased more in the cities in which there were more Airbnb offers. This pattern follows the 2000-2010 trends in hotel employment in Germany, for the same cities. This shows that in the 2 years period since Airbnb is present in Germany, there is no evidence of Airbnb correlating with les employment in the hotel sector. However, that is not to say that on the medium or long run there will be no effects on hotel employment, especially if Airbnb will continue to expend. On the other hand, cities already started developing regulations for short term rentals, which, on the medium run, can impact the growth of such businesses. For example, in May 2016, Berlin started enforcing a regulation according to which landlords need permits in order to rent their spare space for short term and it is permitted to do so only if one rents less than 50% of the space[8]. Other cities, like Hamburg, have much more permissive Airbnb-related policies. Some cities did not yet established rules for short-term rentals. The content of such regulations and their friendliness towards the sharing economy companies and hosts will affect the way Airbnb and similar platforms develop. Thus, further

[8]Berlin Bans Most Airbnb-Style Rentals CityLab. (2016). *Berlin Bans Most Airbnb-Style Rentals*. [online] Available at: http://www.citylab.com/housing/2016/04/airbnb-rentals-berlin-vacation-apartment-law/480381/ [Accessed 15 Jul. 2016].

research is needed in order to assess to long term effects of Airbnb and considering the policy side will be essential.
The employment type does not seem to be affected by the presence of Airbnb. If the premise is that Airbnb impacts hotels revenue, then the consequence would be less employed people and less full-time employees. However, evidence shows that after 2012 the employment type was not affected by the presence of Airbnb in a city. The full-time employment positively correlates with the Airbnb penetration score. However, the time effect is not taken into account when looking at employment type and there are several alternative explanations for which full-time employment in the hotel industry is more frequent in cities in which Airbnb penetration is higher – namely the presence of more and larger hotels or significant touristic activity within the local economy.
The most interesting finding of this paper regards the wage effects in the hotel sector. My analysis shows that daily wages are 2% to 6% less in cities with high Airbnb penetration and after 2012. This effect is stronger when we look only at full-time employees – from 1% when only the time effect and Airbnb penetration are considered, to a constant 4%-5% when other control variables are added. The same happens when we only look at small and medium enterprises in the hotel industry. While we cannot claim causal relationships between wages in the hotel industry and Airbnb presence, there is certainly a strong correlation – these results are significant at 0.01. However, I only looked at 20 cities in Germany, thus the results cannot be generalized worldwide. As stated above, further research should add policy effects in the model and should look at a larger time period.

In terms of operational outcomes, this research paper could be relevant both for the industry and policy makers, as it brings evidence on potential effects of Airbnb for the hotel sector. Being one of the first papers to assess such effects, it could help shaping a general strategy in order to tackle potential negative effects of the sharing economy, like job-loss/job destruction or to imagine solutions for precarisation of labour in certain sectors, if indeed wages would be affected on the long run. While further research is needed in order to fully assess these effects, the paper brings added value, as it shows that the concerns in regard to how the sharing economy affects labour markets and traditional business models are not to be neglected, even if only wages are affected up to now.

References

Airbnb Economic Impact (2014), available at http://blog.airbnb.com/economic-impact-airbnb/

Arntz, Melanie, Terry Gregory and Ulrich Zierahn (2016), *The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis*, OECD Social, Employment and Migration Working Papers No. 189, available online at http://www.zew.de/en/publikationen/the-risk-of-automation-for-jobs-in-oecd-countries-a-comparative-analysis/ , last accessed on July 21st 2016.

Botsman R. and Rogers R. (2010) - "*What's Mine is Yours: How Collaborative Consumption is Changing the Way We Live*", Harper Collins, 2010.

Bruegel (2014) blog post, available at http://bruegel.org/2014/07/chart-of-the-week-54-of-eu-jobs-at-risk-of-computerisation/ last accessed on March 3rd 2016.

Chilton REIT Team (2015), "The Effect (If Any) Of Airbnb On Hotel Companies", available at http://www.nasdaq.com/article/the-effect-if-any-of-airbnb-on-hotel-companies-cm526409#ixzz47h7FrKRk

Crain's Chicago Business, (2015). How much can you really make on Airbnb?. [online] Available at: http://www.chicagobusiness.com/realestate/20150515/CRED03/150519869/how-much-can-you-really-make-on-airbnb [Accessed 2 Nov. 2015].

Data products of the IAB (2012), Catalogue of the department IT Services and Information Management, IAB, January 2012.

Degryse, Christophe (2016) – "Digitalisation of the economy and its impact on labour markets", Working Paper 2016.02, European Trade Union Institute, available online at: http://www.etui.org/Publications2/Working-Papers/Digitalisation-of-the-economy-and-its-impact-on-labour-markets last accessed March 11th 2016.

Edelman, Benjamin G. and Luca, Michael (2014)," Digital Discrimination: The Case of Airbnb.com".Harvard Business School NOM Unit Working Paper No. 14-054. Available at SSRN: http://ssrn.com/abstract=2377353 or http://dx.doi.org/10.2139/ssrn.2377353

European Parliament Briefing (2015) - The sharing economy and tourism, available at http://www.europarl.europa.eu/RegData/etudes/BRIE/2015/568345/EPRS_BRI(2015)568345_EN.pdf

Felländer A., Ingram C., Teigland R. (2015) – "The sharing economy. Embracing change with Caution", Entreprenörskapsforum, Sweden, 2015, available at http://entreprenorskapsforum.se/wp-content/uploads/2015/06/Sharing-Economy_webb.pdf, last accessed on 27.10.2015

Fraiberger, Samuel P. and Sundararajan, Arun (2015), Peer-to-Peer Rental Markets in the Sharing Economy (October 6, 2015). NYU Stern School of Business Research Paper. Available at SSRN: http://ssrn.com/abstract=2574337 or http://dx.doi.org/10.2139/ssrn.2574337, last accessed on 29.10.2015

Frey C.B. and Osborne M. (2013) The future of employment: how susceptible are jobs to computerization?, available at http://www.oxfordmartin.ox.ac.uk/downloads/academic/The_Future_of_Employment.pdf last accessed on March 4th 2016.

Hotrec (2015), "Levelling The Playing Field. Policy Paper On The "Sharing" Economy", http://www.hotrec.eu/Documents/Document/20151105143558-2015-11-05_Hotrec_Policy_paper.pdf

Huws, Ursula (2013) - Working online, living offline: labour in the Internet Age, in Work Organisation, Labour & Globalisation, Vol. 7, No. 1 (Summer 2013), pp. 1-11 Published by: Pluto Journals Stable URL: http://www.jstor.org/stable/10.13169/workorgalaboglob.7.1.0001 last accessed February 17th 2016.

HVS Consulting & Valuation (2015), "Airbnb and Impacts on the New York City Lodging Market and Economy" (October 15, 2015), Available at: http://www.hanyc.org/wp-content/uploads/2015/10/HVS-Impact-Study-FINAL-Airbnb-and-the-NYC-Lodging-Market-10-27-15-copy.pdf

JPMorgan Chase Institute (2016), 'Paychecks, Paydays, and the Online Platform Economy. Big Data on Income Volatility' available at: https://www.jpmorganchase.com/corporate/institute/report-paychecks-paydays-and-the-online-platform-economy.htm

Kowalski W. (2015) The European digital agenda: unambitious and too narrow, Social Europe, https://www.socialeurope.eu/2015/07/european-digital-agenda-unambitious-narrow/ last accessed on March 12th 2016

Krueger, A., Hall, J (2015). „An Analysis of the Labor Market for Uber's Driver-Partners in the United States", 2015, available online at http://arks.princeton.edu/ark:/88435/dsp010z708z67d last accessed on March 6th 2016

Lee, C. W. (2015) – "The sharers' gently-used clothes" in "Viewpoints on the sharing economy", in Contexts, Vol. 14, No. 1, pp. 12-19. ISSN 1536-5042, electronic ISSN 1537-6052. © 2015 American Sociological Association. http://contexts.sagepub.com. DOI 10.1177/1536504214567860.

Miller, Stephen R., (2014) Transferable Sharing Rights: A Theoretical Model for Regulating Airbnb and the Short-Term Rental Market (October 24, 2014). Available at SSRN: http://ssrn.com/abstract=2514178 or http://dx.doi.org/10.2139/ssrn.2514178

Parigi, P., Cook, C. (2015) - "Trust and relationships in the sharing economy" in "Viewpoints on the sharing economy", in Contexts, Vol. 14, No. 1, pp. 12-19. ISSN 1536-5042, electronic ISSN 1537-6052, 2015 American Sociological Association. http://contexts.sagepub.com. DOI 10.1177/1536504214567860.

PWC (2015), "The Sharing Economy", Consumer Intelligence Series, PricewaterhouseCoopers, April 2015, available at http://www.pwc.com/CISsharing last accessed on 27.10.2015

Quattrone, Giovanni and Proserpio, Davide and Quercia, Daniele and Capra, Licia and Musolesi, Mirco (2016), Who Benefits from the 'Sharing' Economy of Airbnb (February 26, 2016). International World Wide Web Conference. WWW 2016, April 11–15, 2016, Montréal, Québec, Canada. Available at SSRN: http://ssrn.com/abstract=2738731

Richter, C., Kraus, S. and Syrjä, P. (2015) 'The shareconomy as a precursor for digital entrepreneurship business models', Int. J. Entrepreneurship and Small Business, Vol. 25, No. 1, pp.18–35.

Shor, J. (2015) – "Getting sharing right" in "Viewpoints on the sharing economy", in Contexts, Vol. 14, No. 1, pp. 12-19. ISSN 1536-5042, electronic ISSN 1537-6052, 2015 American Sociological Association. http://contexts.sagepub.com. DOI 10.1177/1536504214567860.

Szoc E. (2015) "Du partage à l'enchère: les infortunes de la 'Sharing Economy'", available at http://www.acjj.be/publications/nos-analyses/du-partage-a-l-enchere-les.html last accessed March 1st, 2016

Walker, E (2015) – "Beyond the rhetoric of the "sharing economy" in "Viewpoints on the sharing economy", in Contexts, Vol. 14, No. 1, pp. 12-19. ISSN 1536-5042, electronic ISSN 1537-6052, 2015 American Sociological Association. http://contexts.sagepub.com. DOI 10.1177/1536504214567860.

Zervas, Georgios and Proserpio, Davide and Byers, John, (2016), "The Rise of the Sharing Economy: Estimating the Impact of Airbnb on the Hotel Industry". Boston U. School of Management Research Paper No. 2013-16. Available at SSRN: http://ssrn.com/abstract=2366898 or http://dx.doi.org/10.2139/ssrn.2366898