Competitive effects of Airbnb on the Norwegian hotel market

by

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Preface

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I am solely responsible for any interpretations or errors in the thesis.

Oslo, 30 November 2016

Nora Svarstad Ytreberg

Abstract

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The aim of this thesis is to contribute to the growing literature on the competitive effects of P2P sharing platforms on existing markets, in particular their effect on incumbent firms. I study the case of Airbnb and its effect on the Norwegian hotel market. The analysis is based on a panel data set consisting of monthly hotel data and the number of Airbnb listings in five of the largest Norwegian cities. I first explore the causal effect of the introduction of Airbnb on hotel revenue using a fixed effects model, taking advantage of the variation in the timing of Airbnb establishment across the five cities. I find that a 10 % increase in Airbnb supply decreases hotel revenue by 0.3 %. This effect is around 20 times smaller than the effect on hotel revenue of an increase in hotel supply. However, considering the sharp growth in Airbnb in the latest years, I find that from 2014 to 2015 the increase in Airbnb supply accounted for the same decrease in hotel revenue as the increase in hotel supply. Furthermore, I estimate which hotel segments are most affected, and how the hotels strategically respond to competition from Airbnb. I find that hotels operating in the low and medium price segment are most affected, and that the hotels strategically respond by lowering their prices rather than their occupancy rates.

All calculations and estimations have been conducted using Stata version 13.1.

Table of Contents

Table of Figures

Table of Tables

Introduction

In the last 10-15 years, peer-to-peer sharing platforms have emerged in a variety of markets. These platforms offer modern solutions which are often both cheaper and more user friendly than those of traditional firms. As a consequence, peer-to-peer platforms pose a potential threat to traditional incumbents. If this is the case, the market entry of Airbnb, a provider of short term accommodation and one of the most successful peer-to-peer platforms, should have contributed to increased competition in the hotel market.

However, it is disputed whether Airbnb is actually taking market shares from hotels. Despite the sharp growth in Airbnb in Norway the latest years, Norwegian hotels have reported record sales. According to the Norwegian Hospitality Association, 2015 was a record year for Norwegian hotels, with the prospects for 2016 looking even brighter[1]. The large Norwegian hotels chains claim that they have not noticed the competition form Airbnb. The CEO of the country's largest hotel chain, Nordic Choice, has stated that he does not see Airbnb as a direct competitor to Nordic Choice. His view is that Airbnb is an alternative to those who want a different accommodation alternative than a hotel[2]. This assessment is supported by Per Arne Tuftin, Director of Tourism at Innovation Norway, who claims that Airbnb's customer base is primarily made out of young people and families who traditionally do not choose to stay at hotels[3].

This view is also supported by Airbnb themselves. Even Heggernes, former Airbnb market director for the Nordics, has stated in the Norwegian media multiple times that Airbnb's services cannot be compared to those of the hotels. According to him, Airbnb targets completely different costumers, whose focus is on social encounters and a local experience. Airbnb claims that instead of taking market shares from the hotels, they are "growing the tourism pie, attracting many guests who might otherwise not have come", which makes Airbnb an exclusively positive force for the Norwegian tourism industry (Airbnb, 2016).

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[1] https://www.nrk.no/trondelag/fremgangen-til-airbnb-bekymrer-internasjonal-reiselivsbransje-1.13200124 [Read 29.10.2016]
[2] http://www.aftenposten.no/okonomi/--Airbnb-er-i-ferd-med-a-bli-en-viktig-konkurrent-for-hotellbransjen-60802b.html [Read 02.05.2016]
[3] http://e24.no/privat/reise/voldsom-interesse-for-airbnb-i-norge/23480284 [Read 02.05.2016]

Nevertheless, several analysts have commented that these statements are merely tactics both on the part of Airbnb and the hotels. According to Sigbjørn Tveiteraas, professor in hospitality from the University of Stavanger, it is obvious that a certain competition exists between Airbnb and the hotels, and that it is in both Airbnb's and the hotels' interest to understate this overlap[4]. Tveiteraas stresses that not much research has yet been done on the field, but he assumes that the cheapest hotels are most at risk, considering the low average age of Airbnb costumers.

It is possible that Airbnb and the hotels offer differentiated services, and that an Airbnb stay and a hotel stay are not substitutes. However, my hypothesis is that record sales in the latest years, driven primarily by an advantageous exchange rate of the NOK and increasing interest in Norway as a tourist destination, can explain why Norwegian hotels have not felt the growing competition from Airbnb. Despite the increase in tourism, Norwegian hotel prices have barely changed in 10 years[5]. The hotel market is characterized by tough competition and low profitability. If Airbnb and the hotels are in fact close competitors, this may be felt by the hotel industry if the growth in numbers of foreign guests stagnates.

New technology has spurred an enormous growth in peer-to-peer sharing platforms in the latest years, but there has not yet been done much research on the economic effects of this phenomenon. Whether peer-to-peer sharing is a substitute for the traditional forms of trade in goods and services is interesting not only for the hotel industry, but for several other industries in a variety of markets. Also, the question of substitution is relevant for the discussion of how such platforms should be regulated. If sharing platforms in reality compete substantially with traditional firms, it becomes important to adopt regulation of the relevant markets so that the sharing platforms and the traditional firms compete on the same terms. The purpose of this thesis is to contribute to the small but growing number of studies of the competitive effects of peer-to-peer sharing platforms, by analyzing whether and how the introduction of Airbnb has had an impact on the Norwegian hotel industry.

I use data from Airbnb's web page and hotel data from Statistics Norway over the period from January 2006 to March 2016 in five of the largest Norwegian cities. The hotel data consists of monthly data from 202 individual hotels, and the Airbnb data consists of data from 6249

[4] http://www.aftenposten.no/okonomi/--Airbnb-er-i-ferd-med-a-bli-en-viktig-konkurrent-for-hotellbransjen-60802b.html [Read 02.05.2016]
[5] http://www.aftenposten.no/reise/Prisene-pa-norske-hotellrom-star-stille-847467_1.snd [Read 25.10.2016]

individual listings that were active at the point in time of the data collection, in March 2016. Because Airbnb does not release data for external use, there have not been many empirical studies on Airbnb. The most important trait of my data set is that by collecting data off of Airbnb's web page I am able to measure the supply of Airbnb in each city over time, by using the date when the owner of the listing became a member of Airbnb as a proxy for when the listing was made available on the accommodation market. Furthermore, because I have access to data on the same hotels before and after Airbnb was introduced to the Norwegian market, I can observe how each hotel's own revenues have changed after Airbnb was introduced. As I will elaborate on in chapter 4, these traits are important when it comes to isolating the effect of Airbnb on hotel revenues.

Several identification challenges arise when trying to estimate the effect of Airbnb on the hotel industry, in particular related to selection and omitted variable bias. I attempt to isolate the causal effect of Airbnb by using a fixed effects model as my identification strategy. The fact that I have access to hotel level data also allows me to analyze whether certain hotel segments are more affected by Airbnb than others, in order to check the hypothesis that low cost hotels are more exposed to competition from Airbnb. Furthermore, I analyze whether potential decreases in hotel revenues have materialized in lower prices or in lower occupancy rates.

The thesis is structured as follows. Chapter 1 introduces the sharing economy as a concept, and describes the peer-to-peer sharing scene in Norway, Airbnb in particular. Chapter 2 presents the key characteristics of the Norwegian hotel market. Chapter 3 provides an overview of the existing literature on the subject. Chapter 4 explains my empirical strategy, describes the data set, and introduces my empirical model. Chapter 5 presents the results from my analysis, and chapter 6 discusses the results in light of the existing literature. Chapter 7 summarizes the main findings and discusses their economic significance. Chapter 8 provides some topics for future research.

1. The Sharing Economy

The emergence of the Internet and recent technological advances has led to the rise of Internet platforms which challenge the conventional business-to-consumer model of trade. In recent years, more and more online platforms have emerged based on matching individuals demanding different goods and services with other individuals who are providing these goods and services. Internet platforms lower barriers to become a seller, and lower transaction costs by removing intermediaries.

1.1 Terminology

The term "the sharing economy" is being used to encompass these new "peer-to-peer" matching platforms. Which innovations are comprised in the sharing economy depends on how you define the sharing phenomenon. The word "sharing" emphasizes how many of these platforms take advantage of under-utilized resources by allowing individuals to rent out or lend these resources short-term to other individuals, instead of a transfer of ownership. However, this term has been criticized by many, first and foremost because of a belief that "sharing" implies altruism, whereas the so-called "sharing platforms" are often based on monetary transactions. Second of all, some argue that Uber, TaskRabbit, and other labor platforms do not fit into the sharing category even though they are usually included in this term.

Another commonly used term is "collaborative consumption", coined by Botsman and Rogers in their 2010 book "What's Mine is Yours: The Rise of Collaborative Consumption" (Botsman & Rogers, 2010). They define collaborative consumption as "traditional sharing, bartering, lending, trading, renting, gifting, and swapping, redefined through technology and peer communities." This term is more extensive and comprises platforms with a "collaboration" dimension which is not necessarily based on borrowing or lending between individuals; car cooperatives like Zipcar and public bike services like Vélib are mentioned by these authors as cases of collaborative consumption. Online platforms based on the transfer of ownership of second-hand goods between individuals are also often included in this term.

In their 2016 report on the sharing economy, OECD prefers to use the term "peer platform markets" (OECD, 2016). They define this as "a wide range of new and emerging production and consumption models that involve the commercial exchange of goods and services between peers through Internet platforms". They argue that this term better reflects the commercial focus and the variation in these services, as well as in the type of markets they operate in. Others prefer terms like the "access economy", "trust economy", the "gig economy", the "on-demand economy", and numerous similar expressions, all with strengths and weaknesses. In this thesis I will use a term commonly used in the economic literature;

"peer-to-peer sharing" ("P2P sharing") and "peer-to-peer sharing platforms" ("P2P sharing platforms"). These emphasize one of the key ways in which these platform companies differ from traditional firms; by being based on matching individuals rather than providing the goods and services themselves. Despite the "sharing" connotations, these terms include commercial platforms.

Even though the wording of the above terms gives different associations, they are often used interchangeably. Whether a new company is part of the sharing economy, often merely depends on how the company itself or the media defines it (SIFO, 2016). According to SIFO, many companies define themselves as part of the sharing economy merely to catch the attention of the media and to be a part of a new trend.

1.2 Key characteristics of P2P sharing platforms

Although there is significant diversity among peer-to-peer (P2P) sharing platforms, they share some common characteristics. The P2P sharing platforms are online, two-sided (or sometimes multi-sided) platforms that match independent workers or sellers ("peer providers") with consumers ("peer consumers"). The providers and consumers in this model are equals, and an individual can be both a provider and a consumer on the same platform. The business idea is to take advantage of under-utilized resources of which there is infrequent demand, and the platform facilitates and administrates the transactions. Capital platforms facilitate "secondary", short-term rental (or lending) from individuals who otherwise possess the goods for their personal consumption. They can also facilitate second-hand selling and buying between individuals. Labor platforms help match individuals who need a task or a small job done to individuals who are willing to provide this service.

The companies usually do not themselves own the labor or capital that is provided on their platform. This trait is one of the most important success factors of the sharing economy, because it makes the supply of the P2P sharing platforms often significantly more elastic than that of their counterparts among traditional firms (Cullen & Farronato, 2014). Being able to offer their services only when the demand is high enough has the potential to make these platforms more efficient, and can explain why some of the most successful P2P sharing platforms have emerged in markets characterized by infrequent demand, such as the tourism industry (Airbnb) and the taxi industry (Uber). However, some capital platforms that have been referred to as part of the sharing economy, provide the capital and facilitate the "sharing" of this capital. An example of this is car cooperatives.

Technology is central to the functioning of the P2P sharing platforms. They use online payment systems, and they frequently utilize pricing and matching algorithms and other types of software which makes the service effective and user friendly. The platform companies often make money by charging transaction or membership fees.

Another of the most important traits of the P2P sharing platforms is trust. These platforms are often not subjected to the same regulations as the traditional firms in their respective markets when it comes to consumer protection and safety. P2P sharing is dependent on people trusting strangers, and without this trust the platforms would break down. The platforms have a strong focus on implementing self-regulating mechanisms to ensure this trust; they usually provide insurance, they have clear guidelines, and they put significant resources into consumer support. Last but not least, peer reviews have become an important characteristic of the sharing economy and a crucial part of establishing and maintaining trust in the service.

The P2P sharing platforms allow individuals to transact without costly intermediaries. By allowing consumers to share goods instead of buying them, many of these platforms have led to a both cheaper and more differentiated supply of goods and services. This has the potential to improve consumer welfare by increasing access to goods and services, while reducing costs related to negative externalities like pollution and waste (Benjafaar *et al.*, 2015). There is also an important social dimension to the sharing economy. Many of the P2P sharing platforms are network platforms in which individuals can communicate, share their experiences, and meet other people.

Last but not least, the companies in the sharing economy are characterized by being structured in a way that avoids the regulation put it place in the markets where they operate, most importantly because they do not own much capital or labor, but also because they differ from traditional companies in other respects that makes the existing regulation outdated and poorly suited for these new types of companies.

1.3 The emergence of the sharing economy

Sharing is not a new phenomenon. In most societies before the Industrial Revolution, the economy was based on trade between individuals. The Industrial Revolution brought with it ownership, and consumerism. In the 1990's and 2000's, the Internet re-introduced sharing between individuals. Quickly after the introduction of the Internet, people started sharing information, knowledge, and files, and this content was available to anyone. The operating system Linux, the Internet encyclopedia Wikipedia, the video sharing website YouTube, and the image hosting website Flickr, were all based on voluntary, free contributions from individuals. The first years after the Internet had become widespread, it was largely based on non-commercial sharing. In 1995, eBay and Craigslist were founded. Craigslist started as a service for posting events, but quickly expanded to listings of jobs, housing, and items for sale. Today, individuals can reach other individuals with all kinds of requests, both of commercial and non-commercial nature. Craigslist was originally non-profit, and still claims not to be a principally profit-maximizing company[6]. eBay is an online auction website for consumer-to-consumer and business-to-consumer sales, and one of the first companies to commercialize online peer-to-peer trade by using online transaction systems and charging a transaction fee (Einav *et al.*, 2016). eBay and Craigslist were pioneers when it comes to transforming P2P interactions into potentially profitable commercial companies. They expanded quickly, contributing to making online P2P trade more common and widespread.

Further technological advancement and the emergence of social media enabled the further commercialization and institutionalization of sharing, and sparked the emergence of what we today denote as "the sharing economy". Etsy, launched in 2005, is one of the earliest cases of what we today refer to as a P2P sharing platform, focusing on the buying and selling of hand-made or vintage items. The sharing economy really took off after the global financial crisis of 2008 (Botsman and Rogers, 2010). Airbnb and TaskRabbit launched in 2008, and Uber in 2009. New digital technologies like geo-location and matching algorithms made P2P sharing easier and more user friendly, the rise of smartphones made the platforms available to people everywhere at all times, and online transaction systems made trading through an online platform safe and efficient. Social media have made individuals used to communicating and dealing with each other online. "Sharing" is a well-known phenomenon on social media; people share information, memories, thoughts, and recommendations, often daily on social

[6] https://www.wired.com/2009/08/ff-craigslist/?currentPage=all [Read 14.06.2016]

media pages like Facebook, Instagram, LinkedIn and Twitter. Social media have generally made it possible to know more about the person one is dealing with on a P2P sharing platform. By posting your full name or linking to your social media profile on a P2P sharing platform, potential trading partners can verify information about you and make a more informed decision on whether you can be trusted.

In addition to technological progress and the emergence of social media, a few other factors have been referred to as driving forces behind the rise of the sharing economy. The financial crisis of 2008 has been mentioned by many as a key contributor to the rapid growth in P2P platforms that happened around that time. The economic downturn made many people re-think the necessity of possession, and the demand for durable goods fell sharply (Wang, 2010). The downturn also made earning some extra money through renting out under-utilized capital more attractive. These two forces combined were an important growth factor for the sharing economy. Several analysts also argue that the financial crisis led to a change in mentality among consumers (see, for example, Botsman and Rogers (2010)). They argue that the crisis and what was revealed in its aftermath about the global financial system, made a lot of people tired of consumerism, and that the sharing economy was a reaction to this. Their view is supported by pwc, who in their 2015 report about the sharing economy state that after the crisis, 66 % of consumers claimed that they preferred a materialistic lifestyle with fewer possessions (pwc, 2015). Companies like Peerby use this to their advantage by encouraging people to sell or give away their used items. Increased concern about the environment has also been mentioned as an important factor (see, for example, Botsman and Rogers (2010)). Many P2P sharing platforms promote themselves as environment friendly options to ownership, car sharing platforms in particular[7].

Increased population density[8] has probably made it easier for platforms to survive the crucial starting phase of the sharing company. People will not list their items on a platform where no one is browsing for those items, and people will not browse for items on a page which does not have what they are looking for. Because of this, every platform needs a minimum amount of peer providers and peer consumers in order to be successful, which is called the "critical mass". A P2P sharing platform like Getaround would not work in an area with a small,

[7] See, for example, https://www.hertzbilpool.no/om-bildeling/ and https://www.pwc.com/us/en/technology/publications/assets/pwc-consumer-intelligence-series-the-sharing-economy.pdf [Read 30.09.2016]

[8] http://www.un.org/esa/population/publications/longrange2/WorldPop2300final.pdf [Read 30.09.2016]

dispersed population. People living in such an area would not be willing to travel long distances in order to rent a car, they would rather own one themselves. Increased population density facilitates trade between individuals.

Several analysts also argue that there is an increased desire for community and altruism among the young and educated of today (see, for example, Benjafaar *et al.* (2015) and Botsman and Rogers (2010)). Botsman and Rogers argue that a young person's social status is no longer determined by what she owns, but rather by how she contributes to a more collaborative and social world. A vast number of sharing platforms seem to agree on this position. They often refer to their platform as a "community", and their services as "experiences" which help people to connect with each other in different ways on a personal level. The "young and educated" comprise of a major part of the P2P platforms' user base, and a different mentality when it comes to collaborating and sharing amongst this demographic can help explain the growth these platforms have had in recent years.

Some of the new P2P sharing platform companies have become great successes with revenues comparable to the largest players in their sector. Companies like Airbnb and Uber have millions of customers worldwide, and are being valued at billions of dollars[9]. The most successful P2P sharing platforms are so far marketplaces for large capital assets with a high market value, and which most people possess: property, cars, and human capital. However, most of the companies in the sharing economy are still in a start-up phase, trying to attract customers to attain critical mass and earn a profit, and many companies have already failed. Numerous companies which obtained significant attention from the media and from analysts are struggling, and some have disappeared or completely changed from their original business model. Whether there is a market for sharing other types of assets remains to be seen. Some analysts believe that the hassle and risk related to sharing as opposed to owning limits the potential of the sharing economy to assets with a high market value[10].

However, others are more optimistic in regards to the potential P2P sharing platforms. Munger (2016) goes as far as to refer to the emergence of the sharing economy as equally disruptive as the Neolithic and the Industrial Revolution. He calls this third revolution "the Transaction Cost Revolution". According to Munger, the "preference" for owning is not real,

[9] https://www.bloomberg.com/news/articles/2016-08-05/airbnb-files-to-raise-850-million-at-30-billion-valuation [Read 03.09.2016]
[10] http://www.nytimes.com/2014/08/30/upshot/is-owning-overrated-the-rental-economy-rises.html?_r=0 [Read 03.11.2016]

and as the platforms through new software and other innovations accomplish a driving down of transactions costs, it will be possible to rent almost all durable commodities we now own.

Several questions remain about how much and what kind of impact P2P sharing will have on the economy, and whether growth will continue or stagnate in the coming years. Nevertheless, most analysts agree that the sharing economy will foster more successful sharing companies like Airbnb and Uber in several new markets in the years to come, and this will change the way we think about business and regulation in these markets. Important research is therefore now being done to understand how P2P sharing affects the markets in which they operate.

1.4 P2P sharing in Norway

1.4.1 P2P sharing companies operating in Norway

P2P sharing platforms are appearing all over the world, in a wide range of markets. In the following, I will provide an overview some of the P2P sharing companies that have emerged in different Norwegian markets.

Many of the most prominent, global P2P sharing companies, like Airbnb, Couchsurfing, and Uber, are operating in Norway. CouchSurfing, launched in 2004, was one of the earliest sharing platforms[11]. CouchSurfing is based on sharing in the basic sense of the word; it matches travelers with individuals who can offer a couch in their apartment for free, for one or more nights. Airbnb matches travelers with individuals who want to rent out a room or their entire apartment. Uber is a taxi service which lets individuals with a driver's license and a car pick up individuals and drive them to their destination.

Several Norwegian sharing platforms have also emerged on the Norwegian market. Most of these are in a start-up phase. Finn.no is the oldest and most established Norwegian online P2P sharing platform. It was launched in 1996 by four regional newspapers which saw their classified ads market diminish to the benefit of online ad websites. Finn.no launched Finn Torget in 2003, which is a service for buying and selling between individuals[12]. Finn Småjobber, launched in 2013, is a market place for individuals seeking to offer or execute private services. Around 15 000 tasks ("småjobber") were posted on this platform in 2015[13].

[11] http://www.couchsurfing.com/about/about-us/ [Read 14.06.2016]
[12] http://hjemmehos.finn.no/no/om_oss/historien_var/ [Read 14.06.2016]
[13] http://www.klassekampen.no/article/20160112/ARTICLE/160119991 [Read 14.06.2016]

Finn.no is the most visited Norwegian web site, with almost twice as many page viewings as the largest Norwegian newspapers[14].

Several P2P platform companies have appeared in the Norwegian transport sector. Nabobil provides a platform matching individuals who would like to rent a car with individuals who want to rent theirs out. Other Norwegian transport platforms are Bilkollektivet, a carpooling service, and Haxi, an app for transport services similar to Uber.

With the emergence of sharing platforms in Norway, new business models have appeared which cannot be defined as sharing platforms but which are nevertheless a part of the sharing economy. These are services derived from sharing platforms, such as the start-up companies Lotel, Inkeys and Reserveverten, which offer to facilitate Airbnb rental by taking care of listings, communication with guests, key handovers, cleaning, and other services related to Airbnb rental. These companies facilitate the use of P2P sharing platforms, enabling such platforms to reach a broader customer base.

The companies listed in this section are active companies as of June 2016. Some are established, some newly launched and still trying to achieve critical mass. In the latest year, a relatively large number of retail and food sharing marketplaces have appeared, with similar business models. The Norwegian sharing economy is still in an early phase, and the relatively quickly growing number of similar platforms indicates that there is a "sharing hype" in Norway, which most likely will lead to an increasing number of P2P sharing platforms in the years to come. Because of the fast growing, fast changing character of the sharing economy, any overview of active P2P sharing companies should be considered provisional.

1.4.2 Airbnb

Airbnb, short for "Airbed and breakfast", is a global online community marketplace for accommodation rental. As opposed to traditional accommodation companies, Airbnb does not own hotel rooms; it provides a platform for individuals to list or book accommodation. Airbnb markets itself as a social experience, where the traveler will get the opportunity to "live like a local"[15].

[14] http://www.tnslistene.no/?metric=pi&list_id=1&year=2016&week=3 [Read 14.06.2016]
[15] https://www.airbnb.com/livethere [Read 04.06.2016]

Airbnb makes money by charging a 3 % "host service fee", which covers the cost of processing payments, and a "guest service fee", which covers the cost of running Airbnb[16]. The latter ranges from 6-12 %, depending on the specifics of the reservation. The higher the subtotal, the lower the fee. Airbnb fees are non-refundable, unless the host cancels.

A property listed on Airbnb is called a "listing", an Airbnb community member listing his or her property is called a "host", and an Airbnb community member booking a property is called a "guest".

1.4.2.1 History

Airbnb was founded by Joe Gebbia, Brian Chesky and Nathan Blecharczyk in 2008[17]. The idea came to Gebbia and Chesky in 2007 during an annual industrial design conference in San Fransisco which always left the city's hotels fully booked for months in advance. Gebbia and Chesky decided to earn some extra money by offering inflatable beds in their living room and a home cooked breakfast to three conference attendees. They founded the company with Blecharczyk the year after, focusing on high-profile events where hotel rooms were not able to absorb all the travelers. Within a couple of years, the growth of the company took off, and from 2010 to 2015 it grew by 353 times[18].

According to its website, more than 60 million guests have stayed in one of the 2 million listings, spread out over more than 34 000 cities in 191 different countries worldwide[19]. Both by valuation and by number of rooms, Airbnb has surpassed many of the major global hotel companies. Since the rooms listed on Airbnb are not always available, the number of bookings per year is still far under the largest hotel chains. However, Barclays and other analysts project that Airbnb's exponential growth can lead them to surpass the major hotel chains in guest bookings in only a few years[20]. In June 2016, Airbnb is valued at $25,5 billion, which makes it the 3rd highest valued startup company in the world[21].

[16] https://www.airbnb.com/help/article/384/what-are-the-service-fees [Read 04.06.2016]
[17] http://www.theatlantic.com/business/archive/2013/08/airbnb-ceo-brian-chesky-on-building-a-company-and-starting-a-sharing-revolution/278635/ [Read 04.06.2016]
[18] http://www.businessinsider.com/airbnbs-summer-reach-has-grown-by-353-times-in-5-years-2015-9?r=US&IR=T&IR=T [Read 04.06.2016]
[19] https://www.airbnb.com/about/about-us [Read 04.06.2016]
[20] http://qz.com/329735/airbnb-will-soon-be-booking-more-rooms-than-the-worlds-largest-hotel-chains/ [Read 04.06.2016]
[21] http://money.cnn.com/2015/06/27/technology/airbnb-funding-valuation-update/ [Read 04.06.2016]

1.4.2.2 How it works

Anyone with an Internet connection, including non-members of Airbnb, can view all available Airbnb listings, even those who are fully booked. Only members of Airbnb can create or book a listing. Joining Airbnb is free, as is listing a property. All one needs in order to sign up for Airbnb is an e-mail address and a phone number. A member's profile consists of a profile photo, the member's first name, the date and year the member joined Airbnb, and information about whether the member is verified. Any additional information is optional. Many members choose to provide a description of themselves, including where they live, their interests, profession, language skills, etc., in order to appear more attractive for prospective hosts or guests.

In order to create a listing, the host must provide Airbnb with information about the exact location of the property, which will only be available for the guest when the booking is confirmed. Mandatory information about the property that will be publicly available is the type of property, the room type, and the price per night. The creators of listings are to a large degree free to choose which information about their property they would like to post, but Airbnb has created a step-by-step template for creating listings which most people follow closely. This leads most listings to contain similar information. The majority of the listings include photos and a brief description of the property, information about capacity, facilities, the cancellation policy, extra fees and discounts, and the general location of the property. The listings also include guest reviews and a link to the host's profile. Figure A1 in the appendix illustrates a typical example of an Airbnb listing.

Booking an Airbnb listing is done by checking the availability and requesting a booking. When creating the listing, the host can choose which guests are able to request a booking. The host can choose whether to automatically accept all requests, only accept guests recommended by other hosts, or to manually approve any request. In this way, the host has the possibility to reject requests from members who seem untrustworthy, or make a negative impression in any other way. If the booking is confirmed by the host, the guest pays through the web site. Accepted payment methods are credit card, PayPal, or other country-specific payment methods. Airbnb releases the payment to the hosts 24 hours after the guest checks in.

1.4.2.3 Security

Because Airbnb is, in most countries, not subject to the regulations put in place to ensure consumer safety and satisfaction in the accommodation industry, they have put in place self-regulation mechanisms in order to gain and maintain the trust of their users.

Airbnb is based on trust. Hosts trust strangers to live in their home, and guests trust that the hosts are being truthful about the qualities and facilities of their property. Because Airbnb will lose their costumers if too many people have negative experiences with other members, the company has introduced several measures to increase the trustworthiness of its services. Members can choose to go through an ID verification process, in addition to the mandatory confirmation of their e-mail address and phone number, which involves uploading a photo of a government issued ID. By doing this, the member obtains a “Verified ID Badge” that goes on her profile. A host can choose only to receive bookings from profiles with this badge. In 2013, Airbnb started requiring a random 25 % of all US users to verify their ID, with a plan to expand this to users all over the worlds and to eventually verify all Airbnb members[22].

A member can also link her other social media profiles to her Airbnb profile, for instance to a Facebook or LinkedIn profile. Airbnb encourages their members to post non-sensitive information about themselves when creating a profile, by urging them to “help other people get to know you”[23]. It is also possible for a member to ask her friends to post a reference on her profile.

One of the most important features Airbnb has put in place in order to weed out untrustworthy individuals and maintain user confidence in Airbnb’s services, is peer reviews. They are a characteristic of the sharing economy whose purpose is to circumvent the problem of asymmetric information in the peer-to-peer sharing market. After a completed stay with Airbnb, both the host and the guest can write a review of the stay. Because the host could be tempted to write a review in the same manner as the guest, or the other way around, neither of the reviews are made public until both are written and submitted. The possibility of reading reviews of a listing or a guest works as a quality check.

[22] http://blog.airbnb.com/introducing-airbnb-verified-id/ [Read 23.05.2016]
[23] This message appears when an Airbnb member is creating her Airbnb profile

In addition to these measures, Airbnb provides the hosts with an insurance that covers up to $1 million worth of damage to their property[24]. They have also published Standards and Expectations guidelines, and have put in place a fast responding and comprehensive Help Center and Resolution Center, which answer questions and help solving conflicts.

1.4.2.4 Airbnb in Norway

According to several sources, Airbnb was "introduced" in Norway in 2010 (see, for example, Thornes and Thuve (2015) and Sae-Khow (2016)). It is possible that this means Airbnb started promoting their company in Norway in 2010, which could explain why there were only a very small number of Airbnb listings available in Norway before 2010 (see figures 8a-c in section 4.1.3.4).

It is not possible to determine the exact presence of Airbnb in Norway via Airbnb's web pages. However, Airbnb regularly releases some key figures to the Norwegian press. A mini-report on Norway released by Airbnb also contains some key figures on the Norwegian Airbnb market from 2015 (Airbnb, 2016). At the time of the release of the report, there were 7900 active hosts in Norway, with the average earning of the typical host at around $2600. During 2015, approximately 200 000 guests stayed in Norway through Airbnb, and the average length of stay was 3 nights. Figure A2 and A3 in the appendix illustrate that these Airbnb stays were quite scattered, both over the country and within cities. According to the mini-report, 70 % of guests were from Europe, 13 % from Norway, and 17 % from North America. In Oslo, Bergen, and Tromsø, the three most important countries of origin for guests are the US, Germany and France. Not surprisingly, Stavanger and Trondheim are mostly visited by travelers from Norway, as these cities are not dominated by tourists but rather by Norwegian business travelers.

Figure A4 illustrates the number of active hosts in five of the largest Norwegian cities, and in the rest of the country, in 2015. The average price for an Airbnb stay in Oslo was 721 NOK per night per August 2015[25].

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[24] https://www.airbnb.com/guarantee [Read 25.05.2016]
[25] http://www.aftenposten.no/okonomi/--Airbnb-er-i-ferd-med-a-bli-en-viktig-konkurrent-for-hotellbransjen-60802b.html [Read 02.05.2016]

Airbnb has had an impressive growth in Norway from when it was first introduced in 2010. According to numbers released by Airbnb to the Norwegian press, the number of listings in Norway has increased by an average yearly rate of around 129 %[26]. The Norwegian Ministry of Trade, Industry and Fisheries estimates that per October 2016, Airbnb has a total market share of around 2 % in Norway, measured in total guest nights[27]. Innovation Norway however, estimates that Airbnb accounted for around 1 million guest nights in 2015[28], implying a market share of around 3.3 %.

1.4.2.4.1 Regulation of Airbnb in Norway

In Norway, Airbnb is regulated as "letting of a private dwelling" in the Norwegian tax code[29]. In other words, Airbnb is subjected to the regulations of the regular market for housing rental, which means that individuals can rent out part of their principal apartment tax free, but renting out a larger part or the whole apartment is taxed after revenues exceed 20 000 NOK[30].

The Norwegian hotel industry is concerned with what they describe as competition on unequal terms[31]. The Norwegian Hospitality Association (NHO Reiseliv) claims that a large share of Airbnb hosts is in fact professional, commercial actors, who are renting out apartments they themselves do not live in[32]. According to NHO, neither Airbnb nor hosts operating on Airbnb are paying taxes on their revenues. NHO has provided a list of suggestions of regulatory changes to the Norwegian government, which they believe will contribute to evening out the playing field between hotels and P2P accommodation sharing platforms (Sunde, 2016). Among these suggestions are registration requirements for all accommodation rental activities, a limit on private short term rental of 6 weeks a year, equal requirements for insurance and reporting to Statistics Norway.

When it comes to whether Airbnb's activities should be regulated in a similar way as hotel activities, it is helpful to know more about the degree to which Airbnb is competing with traditional hotels. This thesis will hopefully contribute to that debate.

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[26] http://www.dn.no/nyheter/naringsliv/2016/07/31/1007/Delingskonomi/-folk-lurer-p-om-det-lnner-seg--leie-ut-p-fulltid [Read 02.08.2016]
[27] http://e24.no/digital/airbnb/new-york-slaar-ned-paa-airbnb/23827822 [Read 24.10.2016]
[28] http://e24.no/privat/airbnb/en-million-airbnb-overnattinger-i-norge-i-fjor/23630160 [Read 02.05.2016]
[29] http://www.skatteetaten.no/en/person/Tax-Return/Topic-and-deductions/Housing/letting/Tax-obligation-upon-letting-of-a-private-dwelling/ [Read 03.08.2016]
[30] http://beta.skatteetaten.no/tag/airbnb/ [Read 03.08.2016]
[31] http://www.dn.no/grunder/2015/12/14/1743/Eiendom/lager-minihotell-med-airbnb [Read 20.06.2016]
[32] This is disputed by Airbnb, who claim that 89 % of Norwegian Airbnb hosts rent out space in their primary residence (Airbnb, 2016).

2. The Norwegian Hotel Market

A hotel, according to Statistics Norway, is a commercial establishment which offers short term rental to guests and tourists[33]. This definition does not include short term rental through Airbnb. I consider the geographic market of a hotel to be local, usually the city or vicinity in which the hotel is located. I assume that a guest first chooses which place to visit, then decides which hotel to stay at. Because of high transportation costs related to staying in a hotel removed from the place one wants to visit, each hotel thus competes with other hotels in the same locality. This assumption might hold better in the big cities than for mountain lodges and ski resorts, which may compete regionally or nationally.

The Norwegian hotel market can be divided into three main segments; the leisure segment, the business segment, and the course and conference segment.

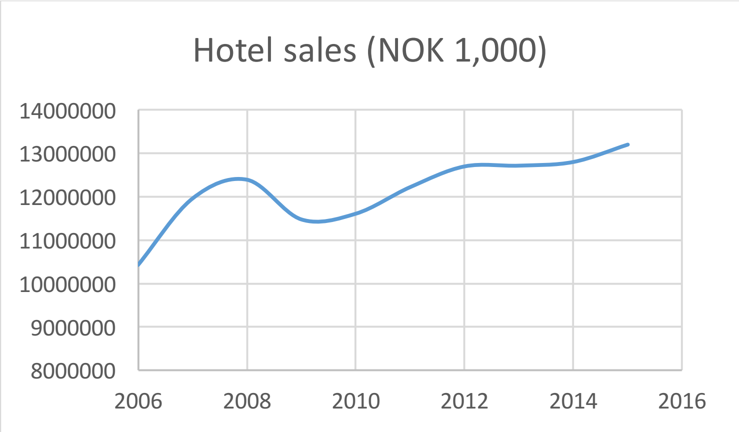
2.1 Key figures

The large hotel chains dominate the Norwegian hotel market. These chains usually operate in several Norwegian cities, often also in the other Nordic countries. In 2015, the largest hotel chain in Norway was Nordic Choice Hotels. Measured as the share of total hotel rooms, their market share was around 14 %. Scandic acquired Rica Hotels in 2014, and thus became the second largest player in the market, with a market share of 13.4 %. Thon Hotel is the third largest player, controlling 8.9 % of the market. These market shares were calculated using the number of rooms listed in each chain's 2015 annual report. In 2013, the nine largest hotel chains controlled 70 % of the guest nights in Norway and an estimated 73 % of room revenues (Horwath, 2015). Because of the merger between Scandic and Rica, the hotel market is probably more concentrated today than it was three years ago.

The Norwegian hotel market had a total revenue of a little more than 13 billion NOK in 2015. Figure 1 shows that total hotel revenue in Norway has been increasing during the last 10 years, with the exception of a sharp dip during the financial crisis of 2008-2009, and a stagnation between 2012 and 2014.

[33] http://www.ssb.no/klass/#/klassifikasjoner/6/koder [Read 21.10.2016]

Figure 1: Hotel sales (NOK 1000) in Norway, adjusted for inflation. Source: Statistics Norway[34]



Over the same period, hotel supply has been growing as well. In 2015, there were 1089 hotels comprising a maximum of 85 081 hotel rooms in Norway. Figure 2 shows that hotel supply has been steadily increasing during the last 10 years. The increase in capacity comes from an increase in the number of beds, rather than the number of hotels. This is because the hotels entering the market are larger than the ones exiting (Horwath, 2016).

Figure 2: Maximum number of rooms in Norway. Source: Statistics Norway[35]

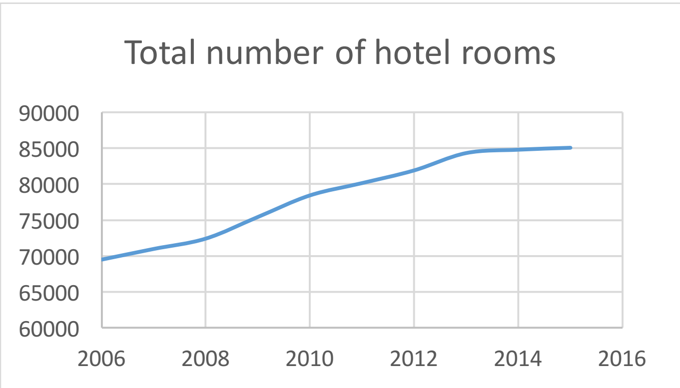


Table 1 presents the composition of the 2015 Norwegian hotel market, by segment. Leisure was the largest segment, making up more than half of the market. This segment grew by 13.1 % between 2014 and 2015. This is due to an increase in tourism to Norway, and a decrease in the business activity in certain Norwegian regions. The willingness to pay is usually higher in the business segment (Hotelia, 2016). The development in the composition of the hotel market is thus important for the profitability of the sector.

[34] Statistikkbanken, table 03615
[35] Statistikkbanken, table 08399

Table 1: Composition of the 2015 Norwegian hotel market. Source: Hotelia, 2015

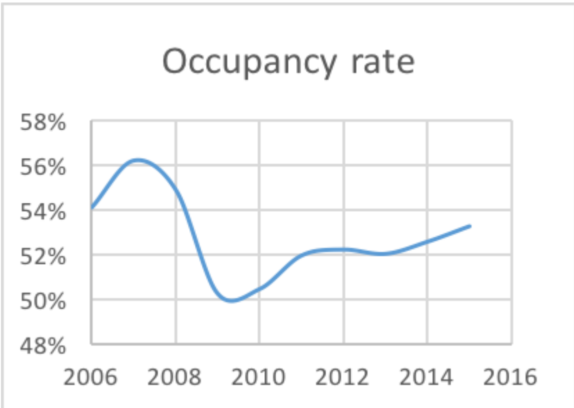
Market segment	Market share
Leisure	51 %
Business	36 %
Course and conference	13 %

The share of foreign stays at Norwegian hotels was 27 % in 2015 (Hotelia, 2015). This was an increase of 11 % from the year before. The most important countries providing tourists to Norway is Sweden, Germany and the United Kingdom. There has also been a large increase in tourism from Asia in the latest years, particularly from China (Innovasjon Norge, 2016).

Figure 3a presents the average price per room over the period, in 2016 NOK, and figure 3b presents the average occupancy rate. Both parameters increased early in the period, and experienced a distinct dip between 2008 and 2009. This dip is probably due to the financial crisis in 2008, which hit the hotel industry hard both because of a decline in tourism and business related travels, as both the global and the Norwegian economy slowed down. Despite a certain degree of fluctuations, the occupancy rate has been relatively stable between 50 and 56 % over the whole period. Prices, however, have been declining since 2008. In 2015, the average daily rate was 916 NOK, and average hotel occupancy was 53 %.

Figure 3a: Price per room, adjusted for inflation. Source: Statistics Norway[36]

Figure3b: Occupancy rate. Source: Statistics Norway



The composition of the market, average prices per room and occupancy rates vary between Norwegian cities. I will take a closer look at this in the descriptive statistics of five of the largest cities in chapter 4.

[36] Statistikkbanken, table 03616

2.2 Key factors affecting the performance of the Norwegian hotel market

The mid-market segment is the largest hotel segment in the Nordic region. The majority of the largest chains operating in Norway focus on this segment, and describe themselves as full-service suppliers, meeting the demand of both leisure and business guests. This segment has historically been less cyclical than other segments, and thus is not as affected by changes in the economic climate (Scandic, 2016). However, Norwegian hotels are still affected by macroeconomic fluctuations, in Norway and abroad.

An important macroeconomic factor for the hotel industry is the economic activity in Norway, closely linked to the oil price. The dramatic fall in oil prices in 2014, slowing down the Norwegian economy, led to a fall in demand from Norwegian business travelers in 2015 (Thon Hotel, 2016). However, the exchange rate of the NOK, another important macroeconomic factor, has developed in favor of the Norwegian hotels. The depreciation of the currency has both been beneficial for the Norwegian economy, limiting the fall in demand from business travelers, and has stimulated both Norwegians and foreigners to choose Norway as a leisure destination (Olav Thon Gruppen, 2016). According to Innovation Norway's competitiveness index, Norway's competitiveness in tourism increased by 11 % from 2014 to 2015. Innovation Norway claims that in addition to the favorable exchange rate, intensive marketing of Norway as a tourist destination has contributed to the growing numbers of hotel guests (Innovasjon Norge, 2016).

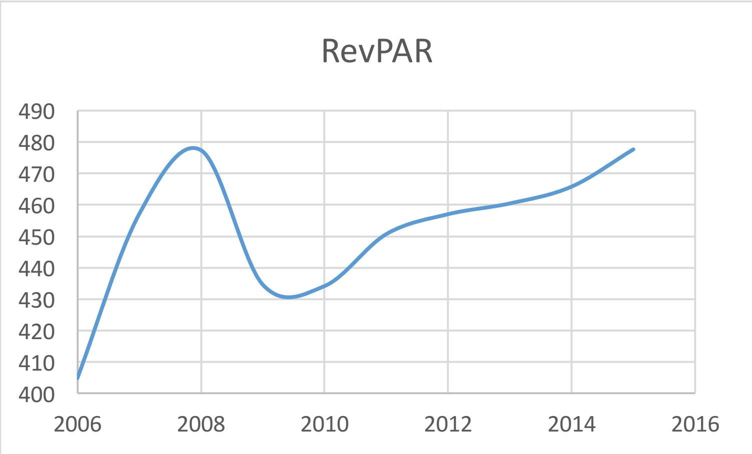
Different parts of the country have been hit differently by the macroeconomic shocks. The fall in the price of oil has especially affected the hotel market in the west coast of Norway, which has a large presence of the oil and gas industry and, because the city is in the region with the largest share of Norwegian stays relative to foreign, it has benefitted less from the favorable exchange rate of the NOK. Revenue per available room in Stavanger, the most important city in Norway for the oil and gas sector, has more than halved since 2014[37].

Even with a low oil price and with capacity increases, the total Norwegian hotel industry has been performing well in the last years. The total numbers of room nights at Norwegian hotels increased by 6 % from 2014 to 2015 (SSB, 2016). However, because of the increase in

[37] http://www.dn.no/nyheter/naringsliv/2016/10/10/2147/Reiseliv/ni-av-13-byer-gikk-i-pluss [Read 10.10.2016]

capacity in the latest years, total revenue per available room, a key performance metric in the hotel industry, has not yet reached 2008 levels. This is shown in figure 3c. Even though there is growth in the market as a whole, individual hotels are struggling. As shown in figure 3a, prices have been declining since 2008. According to NHO, 1 out of 3 hotels do not make money[38]. These numbers show that competition in the Norwegian hotel market is strong.

Figure 3c: Revenue per available room. Source: Statistics Norway[39]



3. Literature Review

My study contributes to the existing literature on the effects of the sharing economy on existing markets, specifically the effects on incumbents, on consumer surplus and on total welfare. Although the hotel market differs from many other markets in that the costumer's choice is not between owning and renting, existing research on the effect of P2P platforms on ownership is relevant for my analysis because it provides insight into the degree to which P2P sharing platforms have a potential as an alternative to the more traditional forms of trade in goods and services.

[38] http://www.dn.no/nyheter/naringsliv/2016/10/24/2019/Reiseliv/30-kroner-dyrere-pa-ni-ar [Read 24.10.2016]
[39] Statistikkbanken, table 06211

3.1 The sharing economy in Norway

Research on the attitudes and experiences of the Norwegian people towards the sharing economy can provide insight into the future potential of P2P sharing platforms to compete with traditional firms.

Most Norwegians have high access to digital technology. According to Statistics Norway, 97 % of Norwegian households had access to Internet in 2015, and 91 % have access to broadband Internet[40]. 85 % of the Norwegian population owns a smart phone, and 92 % of people in the age group 25-24 years use Internet on their phone[41]. These numbers indicate that there are no barriers to the potential of online sharing platforms in Norway when it comes to access to the necessary technology.

The Norwegian National Institute for Consumer Research (SIFO) published a report in 2016 on the sharing economy in Norway, including a survey of Norwegians' attitudes and experiences regarding sharing, re-use, digital sharing platforms and user reviews (SIFO, 2016). This report is important with regards to understanding the potential digital P2P sharing platforms has in Norway. However, since the survey only had 1504 respondents, the results must be seen as merely indicative.

High access to digital technology, high presence on social media platforms and familiarity with secondary markets lay a strong foundation for the emergence of online P2P sharing companies. SIFO finds that 88 % of Norwegians have heard of at least one specific sharing platform company, which according to SIFO is a relatively high number. 76 % have heard of Finn Småjobber, 42 % have heard of Airbnb, and 41 % of Uber. The best known Norwegian company in the study, except for Finn.no, is Nabobil, which 31 % of the respondents have heard of. However, only 1 % are registered members. 16 % are registered members of at least one of the platforms in the study. The number of respondents who have knowledge of or are member of the different platforms decreases with age.

Around 5.5 % of the respondents are so-called "active members" of an online sharing platform. This constitutes 83 respondents, and the results can thus not be considered representative. They can however shed some light on tendencies among the participants of the

[40] https://www.ssb.no/teknologi-og-innovasjon/statistikker/ikthus/aar/2015-10-01
[41] https://nrkbeta.no/2016/01/09/2-av-3-nordmenn-bruker-ingen-av-de-fem-storste-nyhetsforsidene-pa-mobil-i-lopet-av-en-uke/

sharing economy. The respondents state the potential to save money, the excitement of trying out new services, and environmental purposes as important reasons to participate on online sharing platforms. Among 73 % of these respondents consider the sharing platforms to be better than, or as good as, traditional services. 72 % would recommend the sharing platforms to others.

Among those who have not participated on an online sharing platform, 72 % state their reason to be a lack of knowledge about these services. 25 % state that they want their things or their time for themselves. Only 4 % state that they do not have access to the relevant technology.

This survey shows that a relatively small part of the Norwegian population participates actively in the online sharing economy. However, a large fraction state that they do not participate because they lack information about the services, and those who have participated are generally happy with the services and would recommend them to others. One important, albeit not surprising, result of the study is that younger people to a larger extent take part of online sharing practices. When asked whether they would use an online sharing platform in the future, the youngest respondents were the most positive ones.

Because online P2P sharing is still a relatively new phenomenon, it is not surprising that large parts of the population still is not familiar with these services. High access to digital technology, a young population familiar with online sharing, and generally positive experiences among those who have participated, indicate that that the potential for online P2P sharing is significant in Norway.

3.2 Modeling the sharing economy

Some researchers have already attempted to model which conditions determine the success of P2P sharing platforms, and how the emergence of the sharing economy might affect ownership, consumer surplus and total welfare. This research is in the early stages, and the literature on the subject largely consists of working papers. However, these working papers, coupled with the established literature on multi-sided markets and transaction costs, can provide valuable insight into how P2P sharing platforms can affect existing markets.

3.2.1 Key success factors

In order to explain the emergence of the sharing platforms, it is helpful to recall Coase's famous article "*the Nature of the Firm*" (Coase, 1937). Here, Coase explains the emergence of "the firm" by its potential to reduce and control the transaction costs that the trade of goods and services incurs. There are costs of doing bilateral trade through contracts on a market, other than the price of the good. These transaction costs, which include information costs, negotiation costs and transportation costs, can prevent trade between people if they become excessive. Coase believed that firms exist because by working as middlemen they can reduce these costs, making possible transactions that otherwise could not have taken place. According to Coase's theory, the transactions costs will decide whether a firm organizes a transaction internally or buys the input or service in the open market. Changes in these costs will change the size of the firms. This is often referred to as the "make or buy" decision.

Several researchers have applied this theory when explaining the emergence of the sharing economy, rephrasing the "make or buy" decision into a "rent or own" one (Munger, 2015). The key concept of the sharing economy is providing sharing platforms which reduce the transactions costs of the open market. For instance, the platforms reduce search costs by automatically matching individual buyers and sellers and presenting all options immediately, they reduce information costs by offering peer reviewing systems, and they reduce negotiation costs by providing pricing algorithms. According to Munger, Coase's theory can be interpreted to imply that the very notion of a "firm" may start to erode. If firms exist because of transaction costs, and the P2P sharing platforms are reducing these costs more efficiently, the margin at which it becomes profitable to organize transactions within a firm might eventually disappear. Munger (2016) predicts that this development will inevitably lead to a decrease in ownership and production, and in prices.

The emergence of P2P platforms markets can also be understood by recalling the theory of what is known in the economic literature as "multi-sided markets"; markets in which two or more groups of agents interact via intermediaries, or "platforms" (see, for example, Armstrong (2006) and Rochet and Tirole (2003)). These markets are characterized by cross-group network effects, which means that the groups exert positive externalities on each other. In other words, a crucial component of the utility of the product is given by the number of other users. In the case of Airbnb, the guests benefit from a rich selection of hosts, and the hosts benefit from a large number of potential guests browsing the web site. The success of the platform is dependent on getting both sides on board. This has been referred to in the literature as the “chicken-and-egg problem”.

According to Armstrong, the fact that these platforms must attract customers on each side of the market, creates a downward pressure on prices. However, the magnitude of this effect depends on whether groups choose to use only one platform, which is called “single-homing”, or choose to use multiple platforms; “multi-homing”. In several markets, one group is single-homing and the other is multi-homing. When this is the case, the multi-homing group has no choice but to use the single-homing group’s chosen platform. Consequently, platforms have monopoly power over providing access to their single-homing customers for the multi-homing side. This can create a situation of “market tipping”, where one firm gains increasing popularity, so that it eventually becomes the industry standard, and rivals may fade out (Motta, 2008). Because of these effects, industries characterized by network externalities are particularly prone to dominance, and are therefore associated with the existence of monopolies. Successful P2P sharing platforms like Airbnb might gain monopoly power, making it difficult for new platforms to attract demand. However, in a market with strong network externalities, monopolies are not unambiguously negative for consumers. First of all, single-homing consumers often enjoy low prices because of their positive externalities on the multi-homing consumers. Furthermore, the existence of only one network might benefit consumers by providing more communication possibilities or more complimentary services, increasing the network effects realized by both sides of the market. Thus, the theory of multi-sided markets does not conclude on the effect on consumer surplus of the emergence of platform markets.

Einav *et al.* (2016) have developed a model to identify which conditions are favorable for peer production, and which highlights how peer entry can lead to changes in market structure. Einav *et al.* consider a perfectly competitive market with two types of sellers; dedicated or professional sellers who incur an up-front cost, and flexible or peer sellers who pay no up-front costs but only incur a marginal cost. The model identifies three main conditions that favor peer production. One of them is related to the relative costs between professional and peer sellers; high capacity costs and more frequent low-end marginal costs help peer sellers. A second condition is related to advertising costs; high advertising or visibility costs makes it difficult to compete both for all sellers, but relatively more difficult for peer sellers, because the professionals can spread the fixed advertising cost over a large number of sales. They note, however, that the Internet is generally lowering advertising or visibility costs. The last main condition that favors peer production is variability in demand, because peer sellers provide a more elastic short-run supply.

According to Einav *et al.*'s model, the success of P2P platforms will depend on these main conditions, and how effectively the platform can bring down visibility costs. The model can help explain the success of Airbnb in the hotel market. The up-front costs of building a hotel is large, relative to the marginal cost a peer seller incurs as a host on Airbnb. An Airbnb host's cost of advertising is zero, as every individual host usually does not advertise beyond posting the listing on the website, which is free. Finally, the hotel market is characterized by significant variability in demand, making the elasticity of supply of Airbnb a big advantage over the hotels.

Einav *et al.* conclude in their article that if P2P platforms enter successfully, they will lower market prices, and in the long term crowd out professional sellers. If that is true, my empirical analysis should show that Airbnb has had a negative effect on hotel revenues and prices, and possibly has led to a decrease in hotel supply.

3.2.2 Effect on ownership, consumer surplus and total welfare

Fraiberger and Sundararajan (2016) develop a theoretical dynamic pricing model where individuals in each period make decisions regarding whether to purchase a new car, a used car, or not purchase anything. The authors calibrate their model with US automobile industry data and data from Getaround, a car sharing service. Their results show that P2P sharing leads to a significant shift away from asset ownership as marketplace access grows. They find that used-goods prices fall and replacement rates rise, and gains in consumer surplus range from 0.8 % to 6.6%. They also find that the consumer surplus increases more pronounced for below-median income consumers. These gains in consumer surplus comes from the increase in access that P2P sharing entails, which is especially pronounced among younger people with low incomes.

Benjafaar *et al.* (2015) have designed an equilibrium model of P2P sharing, where, similar to Fraiberger and Sundararajan (2016), individuals make decisions about whether to own or not. The authors reference the case of car sharing, but their model applies more broadly to P2P sharing in other markets. In the model, they let the renter-owner matching probabilities be affected by the ratio of owners to renters, whereas Fraiberger and Sundararajan assume that these probabilities are exogenously specified. Using their model, they are able to compare outcomes in systems with and without P2P sharing, and to examine the impact on a variety of parameters including rental price, the cost of ownership, the owner's moral hazard cost and the renter's inconvenience cost. According to their findings, P2P sharing can lead to both higher and lower ownership levels, depending on the rental price.

Jiang and Tian (2016) develop an analytic framework to examine how a firm should strategically choose its retail price and product quality to respond to P2P sharing. Their model has two periods, where individuals first decide whether or not to own a product, and the owners then decide whether to use the product or rent it. The authors take the perspective of the manufacturer, showing that moral hazard cost and the platform's commission can have a non-monotonic effect on the profits of the original manufacturer of the product, the surplus of consumers, and social welfare. They find that a possibility to rent out a product on a P2P sharing platform increases the value of the product to the customers. This leads to the finding that in the presence of P2P sharing alternatives, the firm will strategically increase its quality, leading to higher profits but lower consumer surplus.

The result of these theoretical studies is not conclusive. When sharing becomes an alternative to owning, this could lead to less ownership, primarily because sharing is usually a cheaper option that owning. This would hurt incumbent firms. However, the possibility of renting out one's possessions could increase the value of owning, leading to more ownership. Furthermore, the incumbent firms may strategically respond to the competition from P2P platforms both by increasing or decreasing their prices. Which effect dominates, might be contingent on the structure of each market. Empirical research on the effect of the sharing economy on existing markets can provide evidence on which theory best describes the reality.

3.3 Empirical studies on the effect of the sharing economy on existing markets

Little empirical research has been done on the effect P2P sharing platforms have on incumbent firms. Most of the available research that has been done has focused on Airbnb, perhaps because this is one of the pioneers of the sharing economy. However, there are some exceptions. Martin *et al.* (2010) and Cervero *et al.* (2006-07) both measure the effect of carsharing on vehicle ownership in North America, based on survey data. Their results indicate that being a carsharing member increases the likelihood that someone gets rid of their car to a statistically significant degree. Aguiar (2015) studies the effect of Spotify on record sales, finding that Spotify streaming seems to reduce permanent downloads of tracks, but to a smaller degree than what is often assumed by the record industry.

Furthermore, Cramer and Krueger (2016) have examined the efficiency of ride sharing services vis-a-vis taxis in 6 US cities. They find that, on average, the capacity utilization rate is 38 % higher for Uber drivers than for taxi drivers. According to the authors, this means that if their fees are linear, Uber could charge 28 % less than taxies and still earn the same revenue per hour. Cramer and Krueger attribute four factors to the efficiency of Uber; its sophisticated, technological matching system, their large scale, their flexible supply model, and the inefficiency of taxi regulations.

3.3.1 Airbnb

3.3.1.1 The economic impact of Airbnb

Airbnb is restrictive with their data and do not release data for external use, other than the occasional key figures distributed to the press. However, Airbnb has conducted some research themselves on the positive economic impact of their services in different cities around the world. They do not provide much information about how the studies are conducted, other than that they "review the findings of host and guest surveys, Airbnb bookings data, and analysis by local economists"[42].

In a summary report of these city studies, Airbnb writes that 91 % of the Airbnb travelers want to "live like a local", and that 74 % of Airbnb properties are outside the main hotel districts[43]. They also find that Airbnb guests stay longer and spend more money than typical visitors, and that 81 % of hosts share the home in which they live. An Airbnb case study of Oslo shows that these results can be generalized to the Norwegian market. According to the study, 24 % of the Airbnb guests to Norway in 2015 would not have come or not have stayed as long without Airbnb, and 53 % spent the money they saved by staying on Airbnb on "goods, shopping, etc." (Airbnb, 2016).

[42] http://blog.airbnb.com/economic-impact-airbnb/ [Read 07.06.2016]
[43] https://www.airbnb.com/economic-impact [Read 07.06.2016]

These results support the claim that Airbnb's services are differentiated from hotel services, and that Airbnb helps "grow the pie" instead of stealing customers from the hotels. The studies also suggest that Airbnb largely benefits local economies by supporting residents and local businesses. Moreover, Airbnb has tried to put a number on their economic contributions to some of their most important markets. According to its estimates, the Airbnb community in Berlin contributed nearly $130 million in total economic activity throughout the city in 2015. In Barcelona, Airbnb claims they generated $175 million in economic activity and supported more than 4000 jobs. However, considering the fact that this study is made for Airbnb and that the research method is not public, these results must be handled with caution.

3.3.1.2 Airbnb's impact on the hotel market

A handful of empirical studies analyze how Airbnb affects the hotel market. My study is a continuation of one of the earlier papers on this subject, a working paper by Zervas *et al.* (2016), in which the authors study Airbnb's impact on hotel revenue in Texas, USA. They gathered data from the Airbnb website, and obtained detailed, monthly data on more than 3000 hotels in Texas from the Texas Comptroller of Public Accounts, covering the period January 2003 to August 2014. The authors state that the hotels are located in "Texas metropolitan areas", but not precisely how many and which areas these are. However, it is clear that there are at least 10 such metropolitan areas. Zervas *et al.* use two different proxies for measuring Airbnb supply; a cumulative measure, and an instantaneous measure, using the date of the first review as a proxy for market entrance. In order to study the effect of Airbnb on hotel revenues in Texas, the authors use a fixed effects model with hotel and time fixed effects. In addition to this model, they use a difference-in-difference-in-differences model to study the effect of Airbnb on hotels' peak pricing power.

Zervas *et al.* estimate that each additional 10 % increase in Airbnb supply resulted in a 0.39 % decrease in hotel room revenue. They estimate that in Austin, the city in Texas with the largest Airbnb presence, the causal impact over a period of five years is in the 8-10 % range. According to their estimations, the hotels in the low-price segment and the non-business segment were the most affected, and the impact was materialized through lower hotel prices. They also found that the effect of Airbnb on hotel revenue was more pronounced during periods of peak demand.

Neeser (2015) replicates the empirical strategy of Zervas *et al.*, in order to study the impact of Airbnb in the Nordic countries (Norway, Finland and Sweden). He uses monthly data over the period January 2004 to May 2015 from Norway and Finland, and the period January 2008 to May 2015 from Sweden. Because of the small amount of pre-treatment observations from Sweden, this country is often excluded from the regression. Unlike Zervas *et al.*, Neeser obtains aggregated hotel data on the county level. Consequently, his model contains county fixed effects instead of hotel fixed effects.

Similarly to Zervas *et al.*, Neeser estimates a negative impact of Airbnb on hotel revenue. However, his estimate is significantly less negative than that of the Texas study. Neeser finds that when Airbnb supply increases by 10 %, hotel room monthly revenue decreases by 0,11 %. Furthermore, this estimate is not significant at the 0.1 level. Neeser finds that hotels respond to the competition from Airbnb by lowering their prices. This estimate is significant at the 0.05 level, and is almost identical in magnitude to the estimate of Zervas *et al*. Neeser does not find a significant effect of Airbnb on hotel occupancy.

Neeser mentions several possible reasons why, unlike Zervas *et al.*, he did not find a significant effect of Airbnb on hotel revenue. Firstly, the fact that he measures the impact on a greater area, counties versus metropolitan areas, could bias his estimates. Neeser's aggregate area also include large rural areas, where Airbnb has a very limited presence, if any. By measuring the impact on metropolitan areas, Zervas *et al.* can estimate a more local effect. Secondly, the estimated net impact of Airbnb can be biased upwards because Neeser does not observe hotels individually, and thus is not able to single out whether some types of hotels are more affected than others. It is also possible that the difference in the impact of Airbnb on hotel revenues between the studies is related to differences between Texas and the Nordic countries that are not accounted for in their models.

Jordet and Lehne (2016) have replicated the Texas study on the Norwegian hotel market in their master's thesis, using monthly hotel data supplied by Statistics Norway. This study was published some months after I had started on my empirical analysis. Jordet and Lehne have obtained hotel data from 28 of the largest municipalities in Norway, over the period January 2003 to February 2016. However, unlike Zervas *et al.*, Jordet and Lehne have aggregated data on the municipality level, and have thus included municipality fixed effects in their model.

They have also chosen to limit their Airbnb data set to listings posted by “unique hosts”, in an attempt to limit the Airbnb supply measurement problem.

Jordet and Lehne estimate that a 10 % increase in Airbnb supply leads to a 0.4 % decrease in hotel revenue. This estimate is significant at the 0.05 level, and almost identical to that of Zervas *et al*. When studying their whole sample, Jordet and Lehne did not find a significant effect on price, but they find a very large effect on occupancy rates. However, they suspected that including many municipalities with a very small presence of Airbnb might introduce noise to their estimates. When including only the 10 municipalities with the largest presence of Airbnb in their regression, they estimate a price effect in line with the Texas study, significant at the 0.05 level. However, they still find a large, significant negative effect on occupancy rates, unlike the results of the Texas study. The fact that Jordet and Lehne and Zervas *et al.* identify very similar results on Airbnb’s effect on hotel revenue, indicates that Zervas *et al.*’s results might be generalized to the Norwegian market.

Farronato and Fradkin (2016) develop a theoretical framework for an accommodation market structure with dedicated and flexible supply, and differentiated products. The model has a short run and a long run component. The short term component determines daily prices and rooms sold as a function of dedicated and flexible capacity. In the long term component, flexible sellers decide whether to enter the market as a function of pre-determined hotel capacity and the distribution of demand states. The model predicts that hotel profits, prices and occupancy rates are lower when Airbnb capacity is higher. Also, for the same level of Airbnb capacity, the reduction in hotel profits will be relatively larger the larger the hotel capacity constraint. This comes from the fact that if accommodation demand is high relative to supply, this puts an upwards pressure on prices, which attracts more flexible suppliers. An increase in flexible supply reduces the hotels’ residual demand. Capacity constrained hotels have inelastic supply curves, and thus this demand shift causes prices to fall.

Farronato and Fradkin test the predictions of this model empirically, using data provided by Airbnb and hotel data on the 50 largest US cities for the period between January 2011 and December 2014. They find that constraints to hotel capacity are good predictors of Airbnb penetration in a city, with the cities with larger constraints experiencing a larger traction for Airbnb. Accommodation demand is also an important predictor or Airbnb growth; the authors find that Airbnb is bigger in cities where the fluctuations in the number of arriving travelers are large. Farronato and Fradkin also use a model similar to that of Zervas *et al.*, in order to study peers' effects on hotel revenue, occupancy rates, and prices. This estimate is preliminary, but significant at the 0.05 level, and similar to the estimations of Zervas *et al*. Furthermore, like Zervas *et al.*, Farronato and Fradkin also find a significant negative effect on prices, but no significant effect on occupancy rates. Their theoretical model can explain this effect; because Airbnb mostly impacts hotels in cities with a hotel capacity constraint, the reduction in occupancy rates is limited because the hotels operate on full capacity in any case. Further, when Farronato and Fradkin separate their sample into two groups depending on the level of capacity constraint, they estimate a significant price reduction in the constrained cities, and a decrease in occupancy rates in the non-constrained cities. This finding implies that differences in hotel capacity constraints across cities can explain differences between cities both in Airbnb traction and its impact on the hotel market.

Farronato and Fradkin also develop a structural model of equilibrium in the hotel industry, in order to estimate consumer and producer surplus, and market expansion effects. This model is also estimated empirically. Their results show that Airbnb increases consumer surplus, primarily because peer hosts allow more travelers to book available rooms. The consumer surplus generated by Airbnb is thus higher in the more capacity constrained cities. Another interesting finding from the model is that Airbnb has had a large market expansion effect, which varies greatly across cities. This suggests that Airbnb represents a differentiated product, which some people intrinsically prefer to hotels.

4. Empirical analysis

In this chapter I will explain my choice of method for analyzing the effect Airbnb has had on competition in the Norwegian hotel market. Previous studies on the subject have looked at the effect of Airbnb in other markets, or in the Norwegian market but at the municipality level. My analysis differs from these studies primarily in that it explores the relationship between Airbnb presence and hotel revenues on the Norwegian market, looking at changes in hotel revenue before and after Airbnb introduction at the *hotel level*.

I combine data on the presence of Airbnb and monthly room revenue in five of the largest Norwegian cities to estimate the causal impact of Airbnb on hotel revenues, prices and occupancy rates. Since I observe monthly hotel revenue both before and after Airbnb's establishment, and over a large number of years, I am able to examine how the effects depend on the presence of Airbnb, while also controlling for the endogenous selection of where Airbnb has the earliest and the fastest growth.

In this section, I will begin by explaining my identification strategy, and introducing the model I am using to estimate the causal effect of Airbnb on hotel revenue. In section 4.2 I will present the data, and in section 4.3 I present descriptive statistics that shed light on the model. In section 4.4 and 4.5, I will explain the alternative functional forms and specifications used in my model.

4.1 Identification Strategy

I have access to a panel data set that ranges over a relatively long time period both before and after Airbnb was introduced to the market. I will exploit the sample's spatial and temporal variation to estimate the causal effects of Airbnb establishment on hotel revenues, following a method commonly used in the literature when analyzing competitive effects of entry. This method has been used for instance when analyzing the effects of the introduction of Walmart on incumbents in the retail sector (Arcidiacono *et al*, 2016), the effect of Spotify on record sales (Aguiar, 2015), and the effect of Craigslist on classified advertising services in local newspapers (Seamans and Zhu, 2013).

Fluctuations in tourism demand and hotel supply, the exchange rate of the NOK, travelers' preferences, and many other factors might simultaneously influence hotel revenues and Airbnb presence in Norway. Some of these factors can be controlled for by including them as control variables in the model, while others are unobserved. My hotel panel data set allows me to look at *changes* on the individual hotel level, which helps me to avoid a potentially serious omitted variable bias due to unobserved variables.

The exposition here builds on Angrist and Pischke (2009). To set the model up, let Y_{it} equal some outcome variable of each individual i at time t. Let T_{it} represent a treatment which affects individual i at time t. The observed Y_{it} is Y_{1it} if the individual is treated, and Y_{0it} in the counterfactual outcome; that the individual is not treated. Moreover, U_i denotes an unobservable, time consistent variable which affects both Y_{it} and T_{it}. Suppose further that

$$E(Y_{0it}|U_i, X_{it}, t, T_{it}) = E(Y_{0it}|U_i, X_{it}, t), \tag{1}$$

i.e that the expectation of the counterfactual outcome is independent of the treatment. In other words, the treatment is as good as randomly assigned to the individuals conditional on unobserved factors, U_i, and other observed covariates, X_{it}.

The key to fixed-effects estimation is the assumption that the unobserved factors only vary between hotels, but not over time:

$$E(Y_{0it}|U_i, X_{it}, t) = \alpha + \tau_t + \delta U_i' + \gamma X_{it}, \tag{2}$$

where α is a constant term, τ_t denotes the time effect, δ is the effect of the unobservable variables on the outcome variable, and γ is the effect of the observable variables.

I also assume that the causal effect of the unobserved variables is additive and constant:

$$E(Y_{1it}|U_i, X_{it}, t) = E(Y_{0it}|U_i, X_{it}, t) + \rho \tag{3}$$

This implies

$$E(Y_{it}|U_i, X_{it}, t, T_{it}) = \alpha + \tau_t + \rho T_{it} + \delta U_i' + \gamma X_{it} \tag{4}$$

where ρ is the causal effect of interest. Equation (4) implies:

$$Y_{it} = \alpha_i + \tau_t + \rho T_{it} + \gamma X_{it} + \varepsilon_{ikt} \tag{5}$$

where ε_{ikt} denotes the error term, and

$$\alpha_i \equiv \alpha + \delta U_i' \tag{6}$$

Given the panel data, the causal effect of the treatment on the outcome variable can be estimated by treating α_i, the individual fixed effect, and τ_t, the time fixed effect, as parameters to be estimated. This is algebraically the same as estimation in deviations from means, which absorbs the unobserved individual effects[44]. I estimate my model using the regression package

[44] By including individual and time fixed effects, one can estimate the causal effect by transforming the variables into deviations from the mean of each individual. This is called ”within transformation”.

Stata, which automates the deviations-from-means estimator. Stata adjusts the standards errors appropriately, so that the residuals are homoscedastic and serially uncorrelated.

In many panel data models, the unit of observation is more detailed than the level of variation. In other words, outcomes at the individual level are regressed on a shock that applies to all individuals of a group. This can cause a serial correlation problem, because individuals in a group tend to be subject to the same influences (Angrist & Pischke, 2009). Using Stata's "cluster" option may solve the problem, and is standard practice in the literature for analyzing panel data (see, for example, Bertrand *et al.* (2004) and Donald and Lang (2007)).

4.1.1 The model

I am now applying the general model to my panel data set. As a starting point, my estimating equation can be written as:

$$logHotelRevenue_{ikt} = \alpha_i + \rho logAirbnbSupply_{kt} + \varepsilon_{ikt} \tag{7}$$

where i denotes the individual hotel, k denotes the city and t denotes the month and year. The dependent variable is the log of hotel revenue in the main part of my analysis, and the "treatment" in my study is the introduction of Airbnb. Compared to the general model, I have introduced an additional level; I am observing the effect of Airbnb on the revenues of each hotel i, but the treatment is at the city level k. The parameter estimator of interest is ρ, which represents the elasticity of hotel revenue on Airbnb supply. A negative estimator means that an increase in Airbnb supply leads to a decrease in hotel revenue, and a positive estimator indicates that an increase in Airbnb supply will lead to an increase in hotel revenue. ε_{ikt} represents all the other factors that influence hotel revenues.

If $logAirbnbSupply_{kt}$ is correlated with ε_{ikt}, the identification of $logAirbnbSupply_{kt}$ is confounded. Since Airbnb establishment is not random, this correlation cannot be zero. Growth in Airbnb supply is most likely largest where the earning potential is highest, in which case Airbnb supply is positively correlated with hotel revenue. Hotels located in an area with early and fast growth of Airbnb supply might have differences in characteristics which may affect how hotel revenues have evolved over the period, irrespective of the introduction of Airbnb. Intuitively, it does not make sense that hotel revenue would not have evolved over time and differently between hotels if it had not been for Airbnb introduction.

Taking advantage of the variation in the timing of Airbnb establishment across the five cities, I specify ε_{ikt} as a function of hotel fixed effects, $h_{k,}$ time fixed effects, a city-specific time trend τ_t, a vector of additional control variables X'_{ikt}, and a residual error term, v_{ikt}. In addition to the time fixed effects, I include a city-specific time trend, t_k, and an interaction term between the time dummy and a city dummy. The trend eliminates the effects of spurious correlation between Airbnb supply and hotel revenue, and allows variation between cities in unobservables which follow a structural trend. The interaction term allows differences in seasonal variation in hotel revenue between cities. In particular,

$$\varepsilon_{ikt} = h_k + \tau_t + \lambda(t)_k + \gamma' X'_{ikt} + v_{ikt} \tag{8}$$

My key identifying assumption is that the timing and location of Airbnb establishment is uncorrelated with v_{ikt} conditional on the hotel fixed effects, time fixed effects, city trends, and additional control variables. To formalize this notion, I denote by μ_{ikt} the hotel fixed effects for hotel *i*, the time fixed effects at *t*, the city trends and the control variables. Letting $logAirbnbSupply_{kt}$ represent the amount of Airbnb listings that each hotel *i* is exposed to at time *t*, my assumption is that v_{ikt} is conditionally uncorrelated with Airbnb establishment:

$$E[v_{ikt}|\mu_{ikt}] = E[v_{ikt}|\mu_{ikt}, logAirbnbSupply_{kt}] = 0 \tag{9}$$

Substituting for ε_{ikt} using (8), (7) becomes:

$$logHotelRevenue_{ikt} = \beta logAirbnbSupply_{ikt} + h_i + \tau_t + \lambda(t)_k + \gamma' X'_{ikt} + v_{ikt} \tag{10}$$

This empirical model can be understood as a generalization of a difference-in-difference approach, where contemporaneous changes in outcomes are compared between hotels treated by Airbnb and control hotels. The control hotels are hotels that are only barely exposed to Airbnb, and hotel exposed earlier or later over the duration of the data.

In the model I have included $h_{k,}$ a hotel-specific constant which captures the effect of unobservable variables that are constant over time, but vary between hotels. By including this

I allow for time-invariant differences in hotel revenue between the treated and the non-treated hotels. I also include τ_t, a year-month fixed effects variable, which captures the effects of unobservable variables which are constant over hotels but vary over time. However, the fixed effects only control for time-invariant or hotel-invariant factors. I attempt to control for factors that are correlated with both Airbnb supply and hotel revenues, and which vary *both* over time and over hotels, by including them as control variables in the regression. X'_{ikt} is a vector of control variables that vary both in time and space.

Because my unit of analysis is monthly revenue at the hotel level while the treatment, Airbnb supply, occurs at the city level, serial correlation of hotel revenues over time within a city can result in understated standard errors. I correct for this by clustering the standard errors at the city level. All regressions are reported with clustered standard errors.

4.1.1.1 Control variables

Increased demand for accommodation could have lead not only to an increase in the supply of Airbnb but also increased hotel supply, if hotels are strategically built or expanded in areas of anticipated high demand. If this is the case, the increased hotel supply could in itself lead to a decrease in hotel revenue. I control for this effect by including the variable $logHotelSupply_{-ikt}$, which is the total supply of hotel rooms in city k at time t, excluding hotel i's own capacity. I also include hotel i's own capacity as a control, which can change for instance due to renovations.

Changes in demand for accommodation could also bias my estimates upwards. Increased demand for accommodation probably affects both Airbnb supply and hotel revenue positively. If I do not control for this, Airbnb supply will absorb the effect of increased accommodation demand. In addition to the city-specific time trend and the city-month fixed effects, I include the number of passengers at the nearest airport as a proxy for changes in tourism demand.

Changes in the demographics could also potentially affect both Airbnb supply and hotel revenue. For instance, Zervas *et al.* argue that a rise in unemployment could both soften demand for hotels and increase Airbnb supply, because the incentives for people to rent out their homes may increase if they become unemployed. Population and unemployment can also work as proxies for changes in the economic activity across cities. I therefore include the log of population and unemployment as controls.

4.2 Data

In this section, I am describing the data I am using in my empirical analysis.

My full data set consists of monthly hotel data, Airbnb data, and data on unemployment, population and airplane passengers from five of the largest Norwegian cities. The data covers the period January 2006 to March 2016. The hotel data was provided by Statistics Norway's and the population data was retrieved from their web site, the airplane passenger data was supplied by Avinor, the unemployment data by the Norwegian Labor and Welfare Administration (NAV), and the Airbnb data was collected by me from Airbnb.com.

When these individual data sets are merged, I obtain a panel data set, which means that it contains repeated observations over the same hotels, collected over the period. The final, merged data set contains 18,118 hotel-month observations.

4.2.1 The hotel data set

The hotel data was prepared by Statistics Norway for this thesis and consists of monthly hotel data from five of the largest cities in Norway, from January 2006 to March 2016 (10 years and three months in total, or 123 time periods). The data set in unbalanced, which means that not every hotel has observations for every time period. The median number of monthly observations registered per hotel is 123, and the average number is 110. In other words, most of the hotels are observed through the whole or most of the period. The reason why some hotels have fewer observations could simply be that a hotel enters or exits the market during the period, or that it has failed to submit the data for some reason.

All accommodation establishments in Norway have to report some key figures to Statistics Norway every month. Before 2006, all hotels with a capacity of 20 guests or more were required to provide the data. In 2006, the capacity limit was set to 10 guests. This means that the data after 2006 contains a larger share of the accommodation establishments, and I chose to use data from this year and later to assure comparability of the data. Since 2015, all hotels, independent of capacity, have been required to provide the data. There are no hotels that entered my data set in 2015 which had a capacity of 10 or less. The change in cut-off in 2015 thus does not affect the comparability of my data.

The key figures in the Statistics Norway data include numbers on revenue, utilization of bed capacity, utilization of room capacity, and the purpose of their costumers' stay. Only about 5 % of the establishments do not respond. After dropping a few hotels with ambiguous reporting and very few observations, the data set consists of 18 118 observations divided between 202 distinct hotels; 80 in Oslo, 43 in Bergen, 23 in Stavanger, 32 in Trondheim, and 24 in Tromsø.

4.2.1.1 Variables

The hotel data set consists of monthly observations on revenue, number of rooms, number of beds, number of room stays, number of bed stays, and number of customers whose purpose of stay was holiday/recreation, business, or a course/conference.

I constructed the price variable by dividing the monthly hotel revenue by the number of room nights, as advised by Statistics Norway. Monthly capacity was calculated by multiplying the number of rooms of each hotel by the number of days of the month. The occupancy rate variable was constructed by dividing the number of room nights by the capacity.

"RevPAR", or revenue per available room, is a key performance metric in the hotel industry, commonly used in studies on the hotel market. I construct this variable by dividing monthly revenue by the number of available rooms.

4.2.1.2 Strengths and weaknesses

All hotels have to report the key data to Statistics Norway, and according to them, only 5 % do not report each month. I therefore consider the data to be highly reliable and representative of the hotel market in the respective cities. Also, the fact that the hotels are obliged by law to report the data greatly reduces the risk of attrition, which is a common problem with panel data.

Because the data is reported each month, there is considerable variation in the data set, which contains a large number of observations over a relatively long period of time. This reduces the risk of bias in the estimations. The fact that the data is provided at the hotel level makes it possible to analyze in more detail which hotels are affected the most.

The data set has some missing observations, but on a low level. Around 3 % of the observations have missing data on hotel revenue, capacity, and municipality. The problem of missing observations is however largest in the variables indicating the purpose of the stay. Around 13 % of the observations do not contain information about the number of conference stays, around 5.5 % lack information about the number of business stays, and around 4 % do not contain information about the number of leisure stays. The reason for the large number of missing observations in these variables, particularly in the conference stays variable, could be the fact that hotels do not report on this number rather than reporting zero.

Moreover, since the hotels are reporting their data through a questionnaire, there is a risk of measurement error. Statistics Norway writes the following on their website, regarding the accuracy and reliability of their accommodation data: *"In general, errors can occur both when the questionnaire is being completed (respondents submit incorrect information) and during the registration of questionnaires (optical reading)."*[45] Measurement error in the hotel data can lead to inconsistent estimates[46], which may account for my empirical analysis estimating a smaller effect than the true effect of Airbnb on hotel revenue.

4.2.2 The Airbnb data set

The data set consists of data from all of the listings available over the relevant period for Oslo, Bergen, Trondheim, Stavanger and Tromsø, five of the largest cities in Norway.

4.2.2.1 Data collection

I collected all the listings in the five largest Norwegian cities over a 3-week period in March 2016. In order to do this I entered the name of one of the cities in the search field which appears at the front page of Airbnb.com, without entering anything in the "check in" or "check out" fields. This way my search results are comprised both of the listings that are

[45] https://www.ssb.no/en/transport-og-reiseliv/statistikker/overnatting/maaned/2016-11-04?fane=om#content [Read 17.11.2016]

[46] If a variable is exposed to measurement error, it will be correlated to the error term in the model, i.e. $Cov(x,\varepsilon) \neq 0$. See (Angrist & Pischke, 2009) for more on measurement error.

available and those that are unavailable for certain dates. However, an Airbnb search result only includes maximum 300 listings. In order to collect all of the listings I had to refine my search in different ways to make sure that I always had a maximum of 300 results for each search. Another difficulty was making sure that only listings within the city border were included in the search results. In some areas, I had to manually remove listings from outside the city limit.

I collected the data from the listings using the "crawling" software Kimono Lab. This is a software that scrapes information off of web pages, a method increasingly used to monitor the alternative accommodation market (Oses Fernández *et al.*, 2016). Because of variation in the set-up of the Airbnb listings, the software did not manage to collect all the information I needed off of all the listings, and the data set came out imperfect. Scraping all of the listings and manually cleaning the data was a time consuming process.

4.2.2.2 The data set

The data set is comprised of 6249 individual listings; 3847 from Oslo, 1155 from Bergen, 378 from Trondheim, 429 from Stavanger, and 440 from Tromsø. Variables included are "price", "capacity", "number of bathrooms", "number of bedrooms", "number of beds", "property type", "room type", "cancellation policy", "number of reviews", and "date of membership". These variables are chosen because they are specified in most listings, and because they are the ones I consider to be most relevant in deciding a listing's substitutability with a hotel room. The data set is complete and all listings have inputs on all variables. Listings with missing variables were excluded from the data set. These accounted for slightly more than 4 % of the total listings.

In the empirical analysis, the variable "date of membership" is used as a proxy for Airbnb supply. I assume that most hosts create an Airbnb membership at the time when they want to list their accommodation on the website. For every month of every year, I count the number of Airbnb hosts that joined Airbnb before this date. The total "date of membership" of all the listings will hence show the accumulated Airbnb supply. Zervas *et al.* (2016) argue that the exponential growth of Airbnb listings makes cumulative supply correlate strongly with instantaneous supply, which means that "date of membership" is a suitable proxy for Airbnb supply. I also use accumulated capacity and market share as a measures of Airbnb supply. I find accumulated Airbnb capacity by adding up the total capacity of all available listings for every month of every year, and Airbnb market share by dividing the total number of listings by the total number of hotels rooms.

4.2.2.2.1 Strengths and weaknesses

4.2.2.2.1.1 Strengths

4.2.2.3

The data set contains a large number of observations, and allows an insight into the supply of Airbnb in Norway which the company itself has not been willing to provide. It contains rich information about each listing, which allows me to identify the differences in characteristics between the Airbnb markets in the different cities.

4.2.2.3.1.1 Weaknesses

4.2.2.3.1.1.1 Measuring Airbnb supply

By measuring Airbnb supply in a cumulative way, I assume that no listings were taken off the market, temporarily or permanently, since their host first joined Airbnb. If the "date of membership" of a host is January 2010, I assume that the listing was made available on the same date, and has been available since. This is for a lack of information about the exact date the listing was made available and its availability throughout the period.

The assumption has two obvious flaws. First of all, there might be a number of listings that have been available in the past but that are taken off the market and were no longer active at the time when I collected the Airbnb data. In this case, my Airbnb supply measure will understate the real past Airbnb supply, and my estimates of the effect of Airbnb supply on hotel revenues will be biased. A second flaw is that some people might have registered as an Airbnb member long before they made their home available for rent. All information one might want prior to becoming a host can be accessed without joining Airbnb, and thus it is fair to assume that most people with an intention of renting out their home became an Airbnb member with the intention to make their home available within a short amount of time. However, it is also necessary to become an Airbnb member in order to book and pay for accommodation. Consequently, a significant amount of people may have become a member in order to be able to book accommodation, and later decided to put their own home up for rent. If this is the case, my measure of past Airbnb supply will be too large, and the time trend of supply is in reality steeper.

Farronato and Fradkin (2016), who have obtained data directly from Airbnb, have the possibility to construct more accurate Airbnb supply measures than what is possible when merely scraping data off of the Airbnb web pages. However, even with this detailed data, it is not straightforward to measure Airbnb supply. One reason for this is the fact that many hosts do not actively block their Airbnb calendar when their listing is temporarily off the market. Fradkin (2015) finds that between 21 % and 32 % of guests are rejected when they try to book an Airbnb listing, because of this phenomenon. In addition to overstating the true number of available listings, this creates a curious endogeneity problem. The pressure to block the calendar is higher in periods where demand is high, i.e. when each host receives a lot of booking requests. Because of this, the calendar is more accurate during high demand periods, which might result in Airbnb supply appearing lower in those periods than in low demand periods. Farronato and Fradkin have therefore created an adjusted measure of available listings, which is similar to my cumulative measure. The authors claim that even though this measure might overstate the true Airbnb supply, it is a consistent measure of the size of Airbnb over time.

Zervas *et al.* (2016) and Jordet and Lehne (2016) have used two different methods to circumvent the Airbnb supply measurement problem. Jordet and Lehne limit their Airbnb data set to hosts with a single listing ("unique hosts"), because they consider hosts with multiple listings to be more likely to have made one or more of their listings available at a date later than their date of membership. In this way, they attempt to limit the problem of listings that were made available at a different time than their owners' date of membership. This reduces their data set from 8299 to 7022 observations. Zervas *et al.* employ an instantaneous measure of Airbnb supply, in addition to the cumulative measure, using the date of the first review of each listing as a proxy for when it entered the market. They also use this method to identify listings that have not been active for a long period of time.

Because I am not controlling for this possible bias, this Airbnb supply measurement problem has to be kept in mind when interpreting my results, and when comparing them to the results of the empirical studies on the same subject.

4.2.2.3.1.1.2 Missing observations

The Airbnb data set contains a relatively large number of observations, on 10 different variables. All of the available Airbnb listings can be found online, and most of them are included in the data set. However, one possible weakness of the data set is that not all the listings I collected could be included. This was because they had missing values that I could not manually extract either because they were missing in the listing or because the listing had been removed since the URL was collected. Listings with missing values accounted for slightly more than 4 % of the total listings, ranging from 3,5 % of the Tromsø listings to 6 % of the Stavanger listings. I assume that whether a listing had some missing values or was taken offline during this process is completely random. This does not seem like a strong assumption, and in this case the missing listings will not introduce bias in my results.

4.2.2.3.1.1.3 Measurement error

Another weakness in the data set is the possibility of measurement error in some of the variables. When I was cleaning the data set, I came across inputs which were unlikely or contradictory, such as an apartment having only one bed but three bedrooms. In some cases this was due to errors in the crawling process. In the other cases I assume that the error comes from a typing mistake or a misunderstanding made by the host. I managed to detect some of the obvious mistakes, but there might be mistakes left in the data set which are harder to notice. However, I have manually checked many of the listings to make sure the large majority is crawled correctly. Moreover, the only variables that could be incorrectly stated and which I might not have noticed are the numeric variables. This must be taken into account in the interpretation of the descriptive statistics. The variables I assume to the most sensitive to measurement error are the “capacity”, the “number of bedrooms” and the “number of beds” variables.

Another problematic variable is the “price” variable. In the listings, price can both be specified as a flat price independent of the number of guests, or as a price per guest, which often is decreasing in the number of guests. Because the price of the Airbnb listing is sometimes dependent of the number of people staying in the listing, this system makes it difficult to compare prices between Airbnb listings and hotels. Thus, price statistics from the Airbnb data set must be interpreted as merely indicative.

Another factor that is important to keep in mind when interpreting the descriptive Airbnb statistics, is the fact that the data extracted from the listings is information about the listings as of the date they were extracted. Most of the variables are characteristics of the home, like the number of bedrooms and bathrooms, which do not change over time. However, some of the variables, like the price variable, could have changed from the date the listing was first made available on the market. Airbnb even makes is possible to choose automatic price generation from an algorithm which tracks supply and demand. Therefore, some of the descriptive statistics must be seen as a snapshot of the market at the time of the collection of the data, i.e. March 2016.

4.2.3 Additional data

I have collected additional data at the municipality level, which I will use as control variables in my empirical analysis. The unemployment numbers are monthly figures, while the population numbers are quarterly figures. The unemployment numbers are provided by NAV, and the population numbers are retrieved from Statistics Norway's web site[47].

In addition to these data on the demographics, I have data on the number of airplane passengers that fly in and out of the closest airport to each city. I will use this variable as a proxy for tourist demand. For each airport I have monthly numbers of passengers, separated into domestic and international passengers. I have not included passengers that only transfer through the airports.

4.3 Descriptive statistics

In the previous chapter, I assume that there is hotel and time heterogeneity in the data. I also assume that my control variables vary both over time, and between hotels. In this section I will look further into my data, in order to confirm whether these assumptions hold.

4.3.1 The hotel data

In chapter 2, I looked at the situation in the total Norwegian hotel market, from 2006 to 2015. However, the development in the hotel market has been different in different parts of Norway. In the following, I will look at the developments in the hotel market in five of the largest cities in Norway.

Figure 4a illustrates total yearly revenue from 2006-2015 in the five cities. Yearly revenue in the different cities mostly follows the pattern of the total industry presented in chapter 2, with a dip in 2009 following the financial crisis. However, in 2015, revenues sharply increase in

[47] Numbers retrieved from StatBank, table 01223: *"Population at the end of the quarter"*

Oslo while decreasing in Bergen, Stavanger and Tromsø and stagnating in Trondheim. The change in the numbers in 2014 can probably be explained to a large degree by the rapid fall in oil prices that happened in the fall of 2014. Stavanger, which experienced the largest drop in revenues in 2014, has been characterized by a large influx of business travelers connected with the oil industry. A fall in business trips can probably explain a large part of the decline in hotel revenues.

Figures 4b-d show average yearly RevPAR, prices and occupancy rates from 2006-2015 in five of the largest Norwegian cities. Prices and RevPAR start decreasing already in 2007 in both Trondheim and Tromsø, a year before Airbnb introduction. Both parameters increase again in 2009 for all cities except Oslo, where it decreases more or less continuously until 2013. Bergen experiences the sharpest growth after 2009, with annual growth every year until 2014. In 2014, all cities except Oslo experience a sharp decrease. RevPAR and prices in Oslo, however, increase from 2014 to 2015. Occupancy rates follow the same pattern over time, with Bergen and Oslo having the highest occupancy rates over the period, and Trondheim the lowest. Occupancy rates are relatively high in Stavanger over the whole period before they plummet in 2014.

Figure 4a: Total hotel revenue, by city

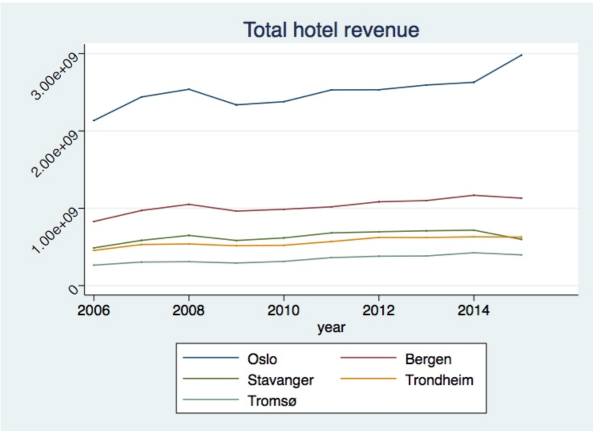


Figure 4b: Revenue per available room, by city

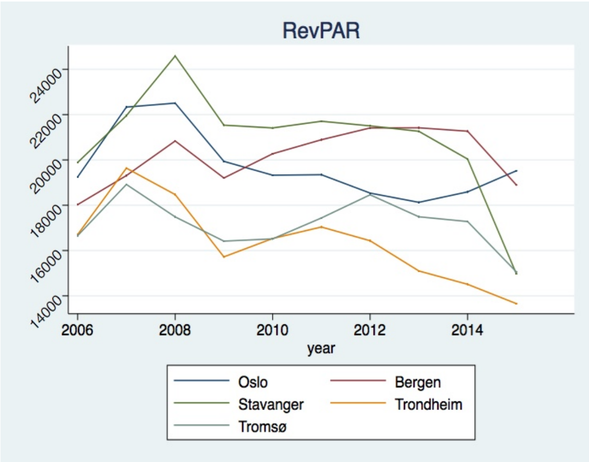


Figure 4c: Average prices, per city

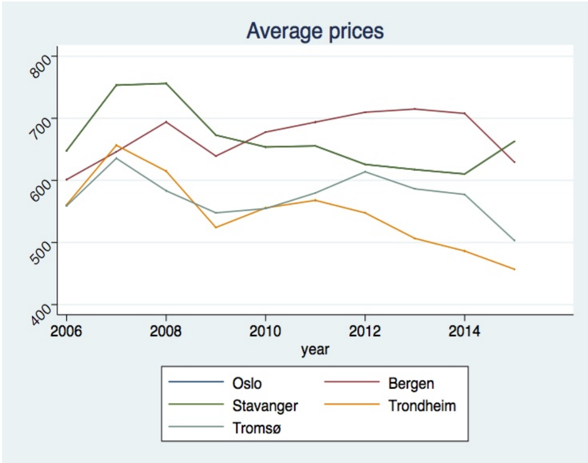
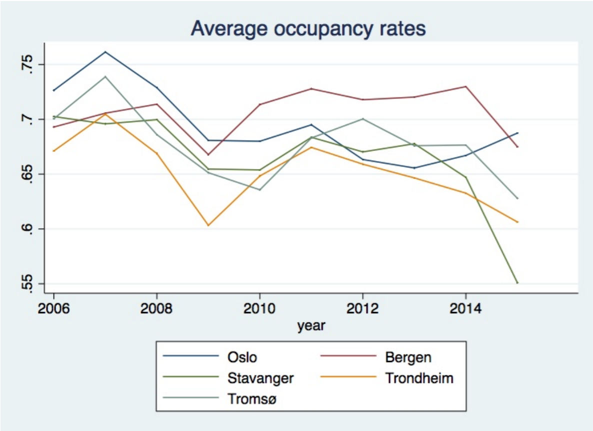


Figure 4d: Average occupancy rates, by city



We can see from these city-specific statistics that there was a difference in the levels of revenues and prices before the introduction of Airbnb on the Norwegian hotel market in 2010, and there has been a development in the accommodation market that cannot only be explained by Airbnb introduction. This was taken into account when choosing my empirical strategy.

The reasons behind these differences lay in the difference in characteristics between the five cities. Figure 5a shows that the hotel room supply varied between the five cities both before and after Airbnb establishment. In all cities this number increases sharply over the period. Because the number of hotels in Oslo was at a considerably larger level than in the other cities in the beginning of the period, this increase can help explain why Oslo experienced the largest decrease in hotel revenue and prices from 2008 to 2014. The other cities all experienced a distinct increase in the number of hotel rooms between 2013 and 2015. This can explain the sharp decrease in occupancy rates in the four cities around this time.

Figure 5b illustrates that the share of business travelers was different both before and after Airbnb establishment between the five cities. Stavanger continuously has the highest share of business travelers, however it decreases from 2008, reaching a share closer to the others by the end of the period. Tromsø has a relatively high share of business travelers in the beginning of the period, but the share decreases over the whole period, and becomes the lowest of the five cities around 2012. In Oslo, Bergen and Trondheim, the share fluctuates throughout the period, and only Bergen reaches a higher share by the end of the period than in the beginning. These differences can be significant when estimating the effect of Airbnb on the hotel market, if Airbnb affects business travelers less than leisure travelers.

Figure 5a: Total number of rooms, by city

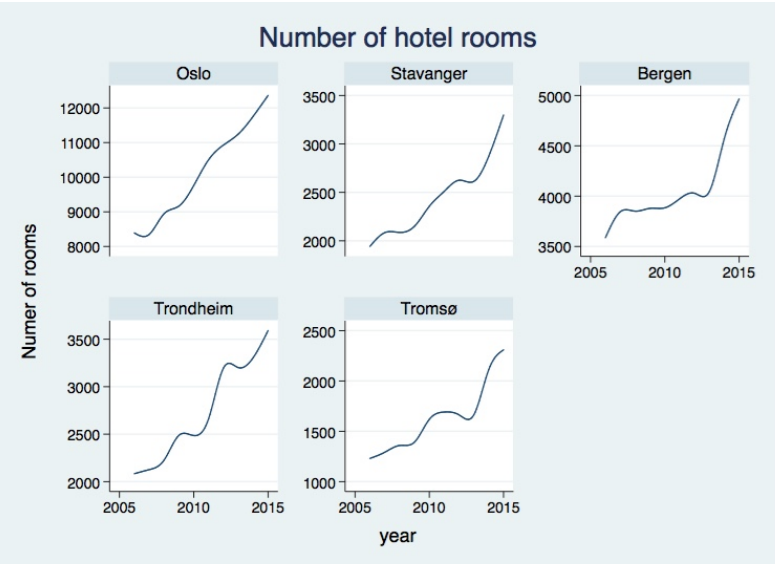
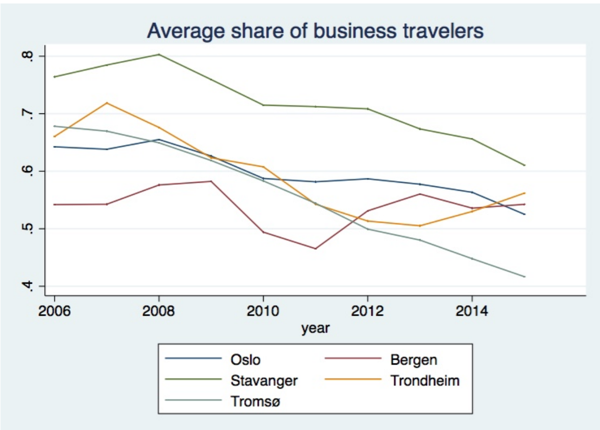


Figure 5b: Average share of business travelers



By including hotel fixed effects, I am controlling for the differences in averages across cities in both observable and unobservable predictors. By including time fixed effects, I am controlling for the factors which have affected all hotel revenues over time, such as the financial crisis and the oil price shock. The fixed effects coefficients absorb the across-group action, leaving only the within-group action, which greatly reduces the risk of omitted variable bias.

4.3.2 City-specific demographics

The five cities also have different demographics, which may have affected how the accommodation market developed over the period. Figures 6a-b illustrate the population and the unemployment level respectively in the five cities. They show that both the population level and the level of unemployment are different between the cities, both before and after Airbnb establishment. Over the period, the population level has been growing in all cities. Unemployment follows a similar trend in all five cities up until 2014, when Stavanger unemployment, which was the lowest for the whole period, suddenly becomes the highest. This can also probably be explained by the fall in oil prices.

Figure 6a: Population, by city

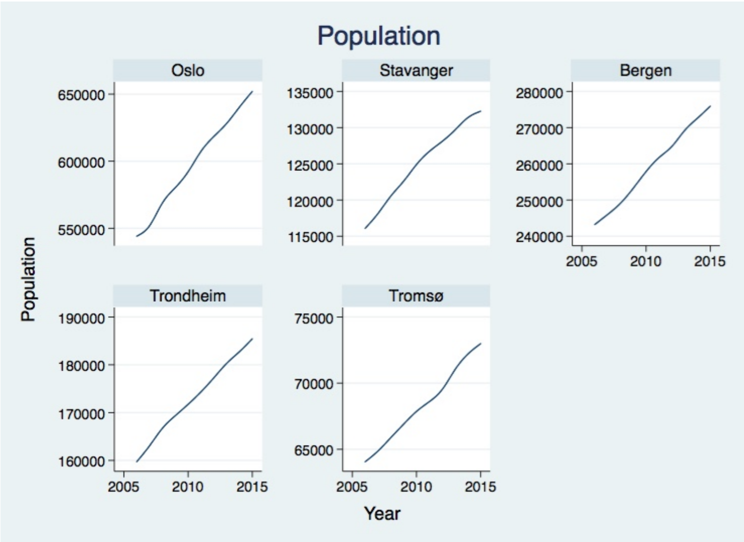
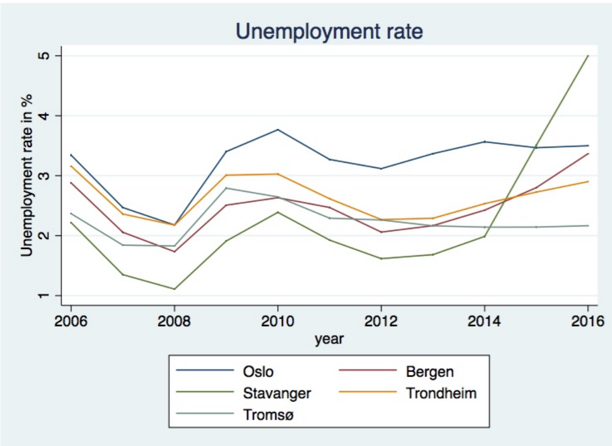


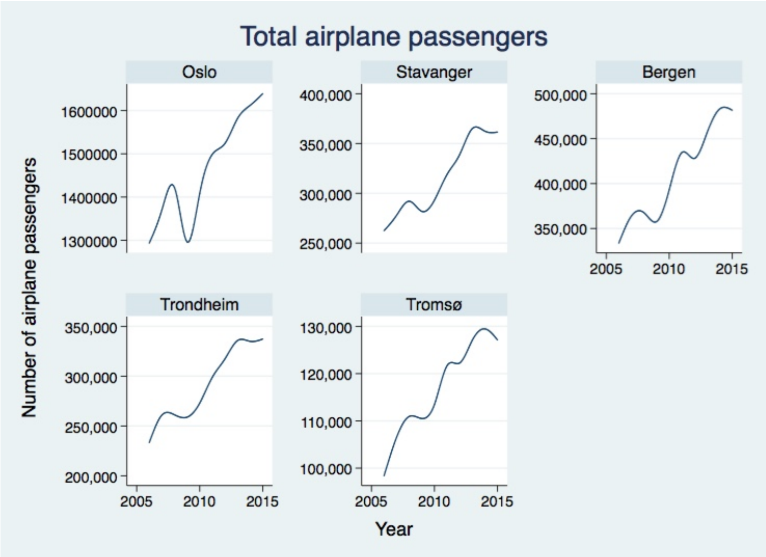
Figure 6b: Unemployment rate, by city



4.3.3 City-specific tourist demand

Different levels of tourism and development of tourist demand are important factors for the performance of the hotel industry. We can see from figure 7 that the number of passengers that fly in an out of the closest airport is much higher in Oslo than in the other four cities, and that all cities have experienced growth in the number of airplane passengers over the period, except for the usual dip in 2009. However, since Oslo started on a much higher level, the increase has been by far the largest in absolute numbers. This can indicate that Oslo has had a greater growth in tourism than the other cities, which would cause an upward pressure on hotel revenue and prices.

Figure 7: Number of total airplane passengers, by city



Demographics and tourist demand change both between cities and over time, which means that their impact is not controlled for by the fixed effects. I therefore include them in the model, in order to avoid omitted variable bias.

4.3.4 The Airbnb data

According to Airbnb data, the average price of an Airbnb listing as of March 2016 in the five cities is 867 NOK. The average capacity is 3,2. The average listing also has 1 bathroom, 1 bedroom, 2 beds, and 29 reviews.

These statistics can hide important differences between cities. Moreover, it is probably misleading to focus on means, as large outliers will affect the means disproportionately. Tables 1a-b present city-by-city statistics, focusing on the median numbers.

Table 2: Median numbers on listing characteristics, by city

	Observations	Price	Capacity	Nb of bathrooms	Nb of bedrooms	Nb of beds	Nb of reviews
Total data set	6248	701	3	1	1	2	5
Oslo	3847	701	3	1	1	2	4
Bergen	1155	703	3	1	1	2	9
Trondheim	378	500	3	1	1	2	3
Stavanger	429	696	3	1	1	2	4
Tromsø	439	804	3	1	1	2	6

The inconsistency between the median capacity and number of bedrooms can have different explanations. First of all, many listings with only 1 bed and 1 bedroom have a capacity of 3 or more, by including a couch or an air mattress as a possible sleeping option. Allowing a larger maximum of people to stay in the accommodation increases the earning possibility of a listing. Another possible reason is measurement error. Some might state the price as including one room, not the whole accommodation. For instance, a host listing his 4 bedroom house might specify that the house has a capacity of 8, but put "1" under "number of bedrooms" because his price is per bedroom and not for the whole house. That way, the average capacity can be inconsistent with the average stated number of bedrooms or beds.

The median price of an Airbnb listing ranges from 500 NOK in Trondheim to 804 NOK in Tromsø. As mentioned, the price variable must be handled with caution, and can only be interpreted as indicative of what price level the listings are on. The price difference between the cities can thus possibly be explained at least partly by measurement error. Another possible explanation could be that the composition of accommodation type and room type is different in the different cities. I will look closer at this in Table 3.

Table 3: Composition of Airbnb supply (in shares)

	Accommodation type			**Room type**			**Cancellation policy**		
	Apartment	House/villa	Other	Whole apartment/house	Private room	Shared room	Strict	Moderate	Flexible
Oslo	0,92	0,06	0,02	0,75	0,24	0,02	0,21	0,31	0,48
Bergen	0,78	0,18	0,04	0,67	0,32	0,01	0,22	0,33	0,45
Trondheim	0,73	0,21	0,06	0,59	0,38	0,03	0,11	0,24	0,65
Stavanger	0,73	0,25	0,02	0,68	0,30	0,02	0,22	0,33	0,45
Tromsø	0,64	0,30	0,06	0,67	0,33	0,01	0,24	0,28	0,49

The city-specific statistics show that the composition of the Airbnb listings are generally quite similar across the five cities. In all cities, apartments are the most common accommodation type. It is most common to rent out the whole home, and very rarely do people rent out a shared room. The most common cancellation policy is “flexible” across the board. However, there are some significant differences. Most noticeably, Oslo has by far the largest share of apartments, and the lowest share of houses. Tromsø, on the contrary, has 24 percentage points more houses among its listings than Oslo. This can explain why the average listing price is significantly higher in Tromsø than in the other cities. Oslo also separates itself by having the largest share of listings that rent out the whole home. Trondheim has the highest share of private rooms, and also has a far higher share of listings with a flexible cancellation policy.

The characteristics of the Airbnb listings in each city can affect how substitutable they are with hotels. For instance, I hypothesize that whole apartments with a flexible cancellation policy are closer substitutes to hotels. These characteristics can help explain possible city differences in Airbnb’s effect on hotel revenue.

Figure 8a-b illustrate Airbnb supply over time in the five cities, measured respectively as the number of listings and as the market share. The market share is measured as the number of Airbnb listings, divided by the number of hotel rooms. The figures show that even though Airbnb was introduced to the global market in 2008, it took off on the Norwegian market only after several years. However, when Airbnb supply starts to grow, it grows exponentially in all five cities. In Oslo, Airbnb growth took off in 2011-2012, in Bergen a couple of years later, and the three last cities, Stavanger, Tromsø, and Trondheim, only experienced a real growth in Airbnb supply around 2015. Today, Oslo has a presence of Airbnb that is many times larger than that of the second largest city, Bergen, measured in the number of listings or in capacity. However, measured as a share of the total market, the picture looks slightly different. Bergen comes closer to Oslo in Airbnb presence when measured in market shares. Also, Tromsø has a relatively large market share compared to Stavanger and Trondheim. Figure A5 in the appendix illustrates Airbnb supply measured as total Airbnb capacity. This figure does not differ much from figure 8a.

Figures 8a-b show that there is considerable variation between the five cities, both in when Airbnb entered the market, and in the total presence of Airbnb in each time period. My empirical model leverages this variation in both timing and presence.

Figure 8a: Number of Airbnb listings, by city

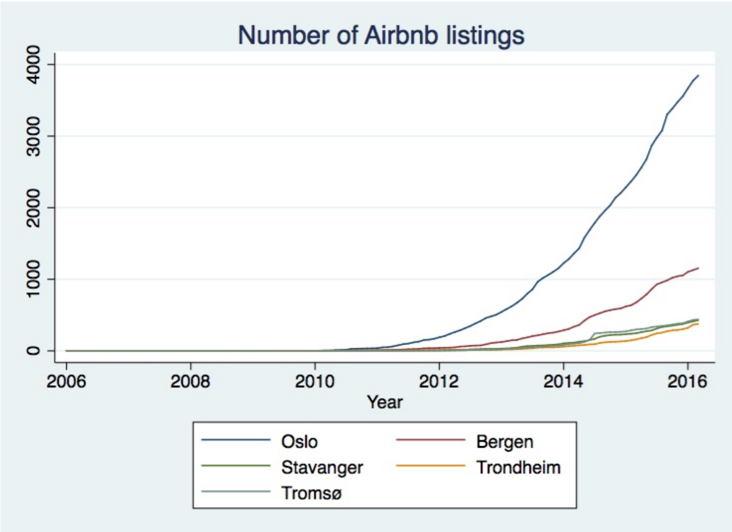
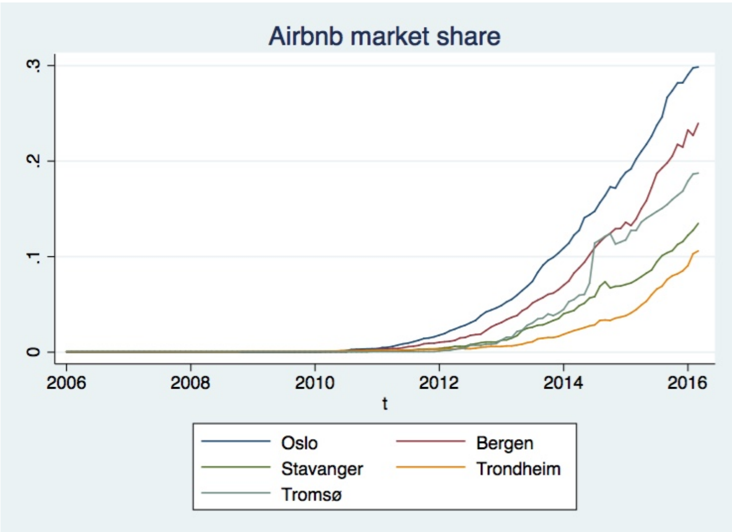


Figure 8b: Airbnb market share, by city



4.4 Alternative measure and functional form of Airbnb supply

I encountered some problems when constructing the variable "Airbnb supply", which meant I had to make some modeling decisions which may have affected my results. I will use alternative functional forms and measures of Airbnb supply in order to check the robustness of my results.

4.4.1 Constructing the Airbnb supply variable

Following Zervas *et al.*, I have used the cumulative number of listings as a measure of Airbnb supply. However, there are alternative ways to measure such supply.

Hotel rooms and Airbnb listings are not directly comparable, and thus no measure of Airbnb supply will be flawless. A hotel room usually takes 1-2 people, sometimes 3 or 4. An Airbnb listing however, can take 16 people or more. Furthermore, it is not certain that five double rooms at a hotel are perfect substitutes to an Airbnb listing with a capacity of ten people. A further complication is that a one bedroom Airbnb listing often at the same time states a capacity of 3 or 4 people, because sleeping arrangements such as a couch in the living room may be counted in. Finally, some cities may have a low number of listings, but a relatively high average capacity of each listing, if a large share of the listings is large summer houses or other accommodation types which may affect the market for vacation rental more than the hotel market.

Taking into account these difficulties of measuring Airbnb supply, I consider the number of listings to be the best measure of Airbnb's presence in a city, because this straight-forward measure minimizes the risk of measurement error. However, in order to check whether varying this measure significantly alters my results, I have replaced the Airbnb Supply measure with the total Airbnb capacity and Airbnb market share.

4.4.2 Log of Airbnb supply

In my total data set, I am including the log of Airbnb supply in each city in each time period. Airbnb supply was zero before Airbnb was introduced to the Norwegian market, and because the log of zero does not exist, taking the log of Airbnb supply is not straightforward. I am solving this by changing the number of listings before Airbnb establishment from 0 to 1. This eliminates the difference between Airbnb supply of 0 and 1, which should not pose a problem, because the difference between the effect of 0 and 1 listing on hotel revenue should be non-existent. This is the method used by Jordet and Lehne (2016).

In order to make sure my method for circumventing the log of zero does not affect my results, I will use a different method and run the same regression. Instead of constructing the log variable as log(Airbnb Supply), I will construct it as log(Airbnb Supply + 1). When Airbnb supply is zero the log variable is now also zero. This is the method used by Neeser (2015)[48].

[48] According to Neeser in personal communication.

4.4.3 Non-constant elasticity of Airbnb supply

Regressing the log of Airbnb supply on the log of hotel revenue assumes a constant elasticity relationship between the two variables. This is probably not realistic, as a 10 % increase of Airbnb supply when it is 1 should have a smaller effect on hotel revenue than a 10 % increase when Airbnb supply is 1000. To see whether this modeling choice affect my results, I will examine whether there is a non-constant elasticity relationship between Airbnb supply and hotel revenue by using the method of Zervas *et al.* (2016). I divide Airbnb supply into four group variables, according to the number of listings which are present in each city in each time period. Then, I construct a dummy variable which indicates which group each city and time period belongs to. Group 1 has zero listings, group 2 has 1-99 listings, group 3 has 100-999 listings, and group 4 has 1000 + listings. Specifically, I estimate:

$$logHotelRevenue_{ikt} = \rho_1 I(Airbnb\ Supply\ 1\text{-}99)_{kt} + \rho_2 I(Airbnb\ Supply\ 100\text{-}999)_{kt} + \rho_3 I(Airbnb\ Supply\ 1000+)_{kt} + h_i + \tau_t + \lambda(t)_k + \gamma' X'_{ikt} + v_{ikt} \quad (11)$$

where I(.) are dummy indicators for the groups. Group 1 is the reference group, omitted from the regression to avoid multicollinearity problems. This model allows for the elasticity of Airbnb supply on hotel revenue to vary depending the number of Airbnb listings.

4.5 Alternative specifications

4.5.1 Including a quadratic variable of interest

Another way of testing whether the effect of an increase in Airbnb supply on hotel revenue is larger when Airbnb supply is large, is to include a quadratic term, $logairbnb^2$. By including this term, I can analyze whether there is a nonlinear relationship between Airbnb supply and hotel revenue. If the marginal effect of Airbnb supply increases with increasing Airbnb supply, the parameter estimate of $logairbnb^2$ should be negative.

4.5.2 Including lag variables

It may not be the case that an increase in Airbnb immediately impacts hotel revenue. People often book their accommodation a certain amount of time in advance, so that the Airbnb supply a month or more before their travel is more relevant to them than the Airbnb supply at the time of travel. Secondly, a listing can be made available at the end of the month, which further decreases the likelihood that it will affect hotel prices in the same month. If there is a lag between the increase in Airbnb supply and the effect it has on hotel revenue, my earlier estimates may be underestimated. I test this by replacing Airbnb supply by a 1 month, a 2 month, a 3 month and a 6 month lag to my regression.

4.5.3 Variation of impact across hotels

The substitutability between hotel and Airbnb accommodation is probably not the same irrespective of the characteristics of the hotel. Some segments of the hotel market might be more affected by an increase in Airbnb supply. For instance, my hypothesis is that low-price hotels are a closer substitute to Airbnb, because Airbnb listings are generally less expensive per person than hotels and may thus be particularly attractive for low budget travelers. Young people, who generally have lower budgets, may also be more prone to using Airbnb because they are more familiar with the sharing economy. Hotels with a focus on business travelers may be less affected by competition from Airbnb, because business travelers seek facilities such as conference rooms that Airbnb listings usually do not provide, because they do not pay for their hotel rooms themselves, because large firms often make deals with hotel chains for their employees, etc.

To estimate these differences in substitutability of different hotel segments with Airbnb, I estimate an interaction effect between hotel type and Airbnb supply:

$$logHotelRevenue_{ikt} = \rho_1 logAirbnbSupply_{kt} + \rho_2 logAirbnbSupply_{kt} \times HotelType_i + h_i + \tau_t + \lambda(t)_k + \gamma' X'_{ikt} + v_{ikt} \quad (12)$$

The coefficient of interest is β_2, which captures the differential effect of Airbnb on the different hotel segments I investigate.

First, I define $NonBusiness_i$ as a binary indicator of whether hotel i is mainly a hotel for business travelers or not. My data set does not contain information of each hotel's facilities, but I do have information on the purpose of each hotel stay. The share of business stays is the number of stays with the purpose "occupation" or "course/conference" divided by the total number of stays. I constructed the variable "*BusinessShare*", which is the total average share of business stays for each hotel.

Because hotels often have a large share of business travelers in the weekdays compared to the weekends, it is not straightforward to define which hotels are focused on business travelers and which are not. I choose to define a "business hotel" as one which has a share of business travelers larger than the share of the hotel at the 75% percentile, which is around 0,7. I believe that this is a rather large share, which means that the estimate of the effect of this hotel segment is conservative. The business hotels serve as the reference group in the regression, which means that the parameter estimate of the interaction term can be interpreted as the effect of non-business hotels on hotel revenue compared to the business hotels.

Second, I define $LowPrice_i$ as a binary indicator of whether hotel i is a low-cost hotel or not. As with the previous sector, my data set does not contain information about whether a certain hotel is a low-cost hotel or not, but it does contain information about the per-room price. As with the binary variable for business hotels, I define a "high cost" hotel to be one which has an average price which is larger than the price of the hotel at the 75% percentile, which is around 715 NOK. The high cost hotels serve as the reference group in the regression, which means that the parameter estimate of the interaction term can be interpreted as the effect of low-cost hotels on hotel revenue compared to the high-cost hotels.

4.5.4 Hotels' response to Airbnb

In the long run, hotels can respond to the competition from Airbnb by building new hotels or shutting old ones down in order to adjust their own supply. In the short run, the hotels can respond either by changing their prices, or by changing their occupancy rate. I will analyze which approach Norwegian hotels have taken by changing the independent variable from hotel revenue to price, occupancy rate, and the number of hotels.

Whether hotels increase or decrease their prices in response to Airbnb competition depends on the price elasticity of the consumers before and after Airbnb establishment. If the price elasticity does not change, economic theory dictates that hotels will lower their prices in accordance with the lower demand. However, it is a possibility that the most price sensitive costumers are no longer in demand for hotels, and thus the remaining demand is less price elastic. In that case, the hotels will respond by raising their prices. According to Farronato and Fradkin (2016), capacity constrained hotels will respond by lowering their prices, whereas hotels that are not constrained will lower their occupancy rates.

I will also check for lags in the effect on prices, in case there is price rigidity in the hotel sector. Because hotel booking usually happens online, hotels often practice dynamic pricing (see, for example, Abrate *et al.* (2011)). Thus, I do not expect there to be a lag in the effect on prices.

Furthermore, I have attempted to replace the dependent variable by the number of rooms each hotel has, to see whether the hotels may have responded to the increase in Airbnb supply by expanding or shutting down parts of the hotel.

4.5.5 Variation of impact across cities

It is possible that an increase in Airbnb supply in one city affects hotel revenues more than an increase in Airbnb supply in a different city. Analyzing which cities are most affected can provide insight into what characterizes an accommodation market where Airbnb gains traction. I allow for such differences by interacting Airbnb supply with a city dummy, using Trondheim as the reference city. Specifically, I estimate:

$$\begin{aligned} logHotelRevenue_{ikt} &= logAirbnb_{kt} + \rho_1(logAirbnb_{kt} \times Oslo) + \\ &\rho_2(logAirbnb_{kt} \times Bergen) + \rho_3(logAirbnb_{kt} \times Stavanger) + \\ &\rho_4(logAirbnb_{kt} \times Tromsø) + h_i + \tau_t + \lambda(t)_k + \gamma' X'_{ikt} + v_{ikt} \end{aligned} \tag{13}$$

This way the coefficients for the interaction variables measure to what extent the effect of Airbnb supply is different for hotels in the other four cities than for Trondheim. Trondheim is chosen as the reference city because the market share of Airbnb is the lowest in this city out of the five.

5. Results

5.1 Comparing the OLS and the FE model

Table 4 presents the results from a simple OLS model in column 1, with city fixed effects added to the model in column 2, and time fixed effects as well as a time trend further added in column 3. In column 4, control variables are added to the model, and in column 5, I further specify the model to include hotel fixed effects.

The simple OLS model, reported in column 1, works as a benchmark for constructing my model. Using the simple OLS model, without trends, control variables, or fixed effects, I estimate a positive coefficient. This is as expected, because there is a positive correlation between hotel revenue and Airbnb adoption which biases my estimate in a positive direction. The fact that the estimate is not significant at the 0.1 level further indicates that this regression is too simple and not suited for detecting the real effect of Airbnb on hotel revenue.

When city fixed effects are added, the coefficient estimate of the log of Airbnb supply turns negative. This result, presented in the second column of table 4, indicates that the positive bias is removed when adding city fixed effects, allowing hotel revenues in different cities to evolve differently irrespective of the presence of Airbnb. However, the estimate is still not significant. Column three presents the results when time-fixed effects, city-month fixed effects, and a linear, city-specific time trend[49] are added to the regression. These variables allow hotel revenues to evolve over time, and differently between cities, irrespective of Airbnb presence. The estimate of the parameter of interest is now more negative, and significant at the 0.1 level. By adding city- and time fixed effects to the model, I have identified a negative, significant effect of Airbnb on hotel revenue.

There could be factors affecting both Airbnb supply and hotel revenues, which vary both between cities and over time. The fourth column of table 4 reports the results from the fixed effects regression in column three, including control variables. The estimator of interest becomes less negative, almost half the size of the estimate in column three. This is for instance due to the effect of controlling for increases in hotel supply. The estimate of the parameter of interest is now significant at the 0.05 level, and so are all of the parameter estimates of the control variables.

[49] *Zervas et al.* include a quadratic time trend, stating that changing from a linear to a quadratic do not significantly alter their results. In my regression, however, including a quadratic trend rather than a linear makes my estimates less significant.

Finally, I include hotel fixed effects in the regression. The results are presented in column five. When controlling for heterogeneity between hotels, I obtain a more negative estimator of interest, which is significant at the 0.01 level. The estimated elasticity for hotel revenue is -0.0307, implying that a 10 % increase in Airbnb listings decreases hotel revenue by 0.307 %. Because the regression in column 5 controls for the most factors, and is highly statistically significant, I apply this regression in my further analysis.

The results of the F-tests reported at the bottom of table 4 also confirm that there is time and hotel heterogeneity in my data.

Table 4: Results from the OLS and FE estimations

VARIABLES	(1) OLS	(2) FE	(3) FE	(4) FE	(5) FE
logAirbnb	0.0163	-0.0107	-0,0453	-0.0252***	-0.0307***
	(0.0122)	(0.0066)	(0.0194)	(0.00383)	(0.00353)
logHotelSupply				-0.581**	-0.737***
				(0.195)	(0.0560)
logRoom				1.126***	0.761***
				(0.0164)	(0.116)
logPopulation				0.391***	0.0537**
				(0.0203)	(0.0153)
Unemployment				-0.104***	-0.0819***
				(0.0166)	(0.0154)
logAirplanePassagers				0.935**	0.903**
				(0.212)	(0.263)
Observations	18,118	18,118	18,118	18,118	18,118
R-squared	0.002	0.074	0.131	0.847	0.417[50]
Time trend	NO	NO	YES	YES	YES
Time FE	NO	NO	YES	YES	YES
City FE	NO	YES	YES	YES	YES
Hotel FE	NO	NO	NO	NO	YES
Prob > F	0.0000	0.0001	0.0000	0.0000	0.0000
Number of hotels					202

In equation (2), (3) and (4), fixed effects are introduced as dummies. Equation (5) is a within transformation.
Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.1.1 Interpreting the control variables

The estimate of the effect of hotel supply on hotel revenue is -0.737. This highly significant estimate means that a 10 % increase in the total supply of hotel rooms is associated with a 7.37 % decrease in monthly hotel room revenue. Intuitively, it makes sense that hotel supply affects hotel revenue negatively, and to a much larger degree than Airbnb. It is interesting to

[50] Because (5) is a within transformation, R^2 here is the ”within” R^2, which explains why R^2 decreases from (4) to (5). When adding a hotel dummy rather than doing a within transfomation, R^2 in (5) becomes 0,905.

note that this estimate indicates an increase in hotel supply has a more than 20 times larger effect on hotel revenue than an increase in Airbnb supply.

The parameter estimate of *logRoom*, the effect of hotel *i'*s own capacity, is positive and significant at the 0.01 level. This is as expected, as a hotel with high capacity should have higher revenues.

The parameter estimate of the log of population is positive and significant at the 0.05 level. According to this estimate, an increase in the size of the population leads to an increase in hotel revenue. The intuition behind this effect is not straightforward. Usually, people do not visit hotels in the city they live in. One possible explanation could be that an increase in population is a result of an increase of the economic activity, which both attracts workers and tourists. In that case, population is a proxy for accommodation demand. Another explanation could be that an increase in the population increases the supply of labor, which depresses wages and thus increases hotel revenues. This is however a small effect that does not a have large effect on my parameter of interest.

The estimate of the effect of unemployment is -0.0819, which means that a 1% increase in unemployment leads to a 0.0819 % decrease in hotel revenue. This estimate is significant at the 0.01 level. As with population, unemployment could be an indicator of the economic activity in a city. This could mean that an increase in unemployment is another proxy for a decrease in economic activity, which according to the parameter estimate leads to a decrease in hotel revenue.

The parameter estimate of the log of total airplane passengers is 0.903, and significant at the 0.05 level. This rather large and positive effect makes intuitive sense, as the variable is a proxy for tourism demand. An increase in tourism should lead to higher accommodation demand, and thus higher hotel revenues.

5.2 Alternative measure and functional form of Airbnb supply

5.2.1 Alternative Airbnb supply measure

The results with the alternative measures of Airbnb supply as the variable of interest are presented in table A1 in the appendix. Column 1 presents the results from my original regression. In column 2, Airbnb supply is estimated as total Airbnb capacity, and in column 3, Airbnb supply is measured as Airbnb's share of the hotel market. The parameter estimate of the variable of interest in column 2 is now less negative than my original estimate; the effect is almost halved compared to my original regression. The parameter estimate in column 3 is positive, and not significant at the 0.1 level. A possible reason why the estimates change when Airbnb supply is measured differently is measurement error. Because of the difficulties in measuring Airbnb capacity and market share, the estimates may be biased towards zero. Furthermore, there is less variation in the market share of Airbnb across cities than in the number of listings, which can help explain why the estimate in column 3 is not significant.

Because the risk of measurement error is less when Airbnb supply is measured as the number of listings, and the estimate in column 1 is significant at the 0.01 level, I will proceed with my original measure of Airbnb supply. However, this is as an indication that my results are sensitive to my choice of Airbnb supply measure.

5.2.2 Alternative log of Airbnb supply

Table A2 in the appendix presents the results of the alternative way of circumventing the problem of taking the log of Airbnb supply. The results show that the choice of method for constructing the log of Airbnb Supply only has a negligible effect on my estimators, and consequently I stick with my original method.

5.2.3 Non-constant elasticity

The results are presented in table 5. I find that increasing levels of Airbnb supply have proportionally larger impact on hotel revenue. There is no statistically significant effect of Airbnb on hotel revenue when the number of Airbnb listings is low, which is what I would suspect. The effect becomes significant when Airbnb supply is at 100 listings or more. The estimate of the effect of Airbnb on hotel revenue when Airbnb supply is 1000 listings or more is also almost three times as large as the estimate of the model with constant elasticity. This model indicates that Oslo, and perhaps Bergen, are the primary drivers of the effect of Airbnb supply that I found in the previous estimations, as these are the only cities which have had periods with more than 1000 Airbnb listings. Excluding Oslo and Bergen from the data gives statistically insignificant estimates.

Table 5: Non-constant elasticity of Airbnb supply

VARIABLES	(1) Non-constant elasticity
Airbnb supply	
1-99 listings	-0.0176
	(0.00989)
100-999 listings	-0.0681**
	(0.0245)
1000+ listings	-0.0815*
	(0.0308)
logHotelSupply	-0.743***
	(0.0801)
logRoom	0.763***
	(0.116)
logPopulation	0.0254
	(0.0243)
Unemployment	-0.0880***
	(0.0159)
logAirplanePassengers	0.901**
	(0.232)
Observations	18,118
R-squared	0.416
Number of hotels	202

All specifications include hotel, city and time fixed effects, and a city-specific, linear time trend
Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.3 Alternative specifications

5.3.1 Quadratic Airbnb supply

Table A3 in the appendix presents the results from this regression. The quadratic term is negative, which would imply that the negative effect of Airbnb supply on hotel revenue is increasing as Airbnb supply increases. However, the parameter estimate of the quadratic term is not significant. Thus, I conclude that including a quadratic term does not improve my estimation, and I will refrain from including the variable in the following regressions.

5.3.2 Lags of Airbnb supply

The results are presented in table A4 in the appendix. The parameter estimates of the effect of Airbnb do not change much when lags are added. The significance level only changes negligibly. The fit of my original specification seems to be the same as when lags are included, and thus I choose to continue with my specification with no lags in the following regressions.

5.3.3 Variation of impact across hotels

The results of the regressions are presented in table 6. Both interaction terms are negative, which means that non-business hotels and low-price hotels are relatively more affected by Airbnb supply than business and high-cost hotels. However, the *NonBusiness* interaction estimate is not significant, which means that I cannot reject the hypothesis that business hotels and non-business hotels are affected in the same way. A possible reason for this could be that it is not possible to segment the hotels into business hotels and non-business hotels in the five largest Norwegian cities by using the share of business stays. This can for instance be because whether a hotel should be defined as a business hotels or a non-business hotel depends on the days of the week and the seasons.

The parameter estimate of the *LowPrice* interaction term, however, is negative and significant at the 0.01 level, which indicates that low-cost hotels are more negatively affected by an increase in Airbnb supply than high-cost hotels. This confirms my hypothesis that low- or medium price hotels are a closer substitute to Airbnb than high cost hotels.

Table 6: Variation of impact across hotels

VARIABLES	(1) Business segment	(2) Price segment
logAirbnb	-0.0266**	0.00182
	(0.00793)	(0.00373)
NonBusiness×logAirbnb	-0.00488	
	(0.00659)	
LowPrice×logAirbnb		-0.0497***
		(0.00262)
logHotelSupply	-0.740***	-0.668***
	(0.0545)	(0.0725)
logRoom	0.761***	0.803***
	(0.115)	(0.0900)
logPopulation	0.0519**	0.0887***
	(0.0164)	(0.0149)
Unemployment	-0.0819***	-0.0624***
	(0.0155)	(0.00642)
logAirplanePassengers	0.902**	0.657**
	(0.263)	(0.158)
Observations	18,118	18,118
R-squared	0.417	0.449
Number of hotels	202	202

All specifications include hotel, city and time fixed effects, and a city-specific, linear time trend
Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.3.4 Hotels' response to Airbnb

The regression results presented in table 7, column 1, show that an increase of 10 % in Airbnb supply leads to a decrease in hotel prices of -0.273 %, significant at the 0,01 level. This result indicates that hotels lower their prices as a response to Airbnb competition, and that their residual demand still consists of price sensitive consumers. Adding lags to the dependent price variable does not significantly change the results, implying that there is no significant price rigidity in this market.

The result is further supported when I replace price with occupancy rate as the dependent variable. Table 6, column 2, shows that the parameter estimate of the effect of Airbnb supply on occupancy rate is negative and significant at the 0.01 level, but less than of third of the size of the price effect. In other words, the hotels seem to respond mostly by adjusting their prices, rather than by leaving their rooms empty.

Finally, I replace the dependent variable with the number of hotels in each city at each period, to see whether hotels have closed or opened as a response to Airbnb competition. This regression does not give significant estimates. I can conclude from this regression that it is not possible to find any long term adjustments in hotel supply as a response to the increase in Airbnb supply. This is not surprising, as it often takes years to plan hotel supply. Zervas *et al.* write that the average estimated time between pre-planning and projected opening of a hotel is approximately four years in Texas. If the time scale is similar in Norway, ongoing projects could have been planned before Airbnb had a significant presence on the Norwegian market.

Table 7: Hotels' response to Airbnb

VARIABLES	(1) Price	(2) Occupancy	(3) Hotel supply
logairbnb	-0.0273***	-0.00757***	-0.00903
	(0.00334)	(0.00122)	(0.00571)
logHotelSupply	-0.719***	-0.204***	0.376***
	(0.0475)	(0.0117)	(0.0570)
logrom	-0.262*	-0.104***	0.00619**
	(0.106)	(0.0226)	(0.00166)
logpop	0.0406*	-0.160	0.0299*
	(0.0174)	(0.677)	(0.0108)
unemployment	-0.0851***	-0.0199	0.00638
	(0.0172)	(0.0114)	(0.0179)
logpasstot	0.933**	0.400*	-0.0451
	(0.278)	(0.155)	(0.0686)
Observations	18,118	18,103	18,123
R-squared	0.357	0.444	0.958
Number of hotels	202	202	202

All specifications include hotel, city and time fixed effects, and a city-specific, linear time trend
Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.3.5 Variation of impact across cities

The results of the regressions are presented in table A5 in the appendix. The estimates of all the coefficients of the interaction variables are negative, which means that an increase in Airbnb supply has a smaller impact on hotel revenue in Trondheim than in the other cities. However, only the coefficient estimates for Oslo and Stavanger are significant at the 0.1 level. Consequently, I cannot reject the hypothesis that Airbnb supply affects hotel revenues the same way in Bergen and Tromsø as in Trondheim.

One possible reason why Trondheim hotels are less affected by Airbnb than in the other cities, is the fact that it has had a relatively small number of Airbnb listings over the whole period, both in absolute numbers and relative to the number of hotel rooms. My results in section 5.2.3 imply that the impact of Airbnb on hotels increases when the number of Airbnb listings increase. This could explain why the Oslo and Stavanger hotels are more affected by Airbnb than Trondheim, as Oslo is the city with the most listings, and in Stavanger Airbnb has had a relatively large market share since its take-off.

Another factor that could explain the differences is the characteristics of each city's Airbnb supply. I hypothesize that Airbnb listings that offer a whole home is a closer substitute to a hotel room than a listing that offers a private or shared room. The fact that Oslo has a larger share of listings that offer a whole home might contribute to Oslo hotels being more affected by an increase in Airbnb supply.

The composition of the hotel market might also explain city differences in the effect of Airbnb on hotel revenue. In section 5.3.3, I could not find evidence that business hotels were more affected by the competition from Airbnb than non-business hotels. However, this result may be a consequence of the difficulties of separating business hotels from non-business ones. Some cities attract relatively more business travelers than others, and are thus more reliant on this segment. Since I hypothesize that Airbnb is dominated by leisure travelers, I expect that hotels located in cities with a large share of leisure travelers relative to business travelers are more affected by Airbnb than those located in cities dominated by business travelers. Trondheim has had a larger share of business travelers than Oslo over the whole period, which can explain why Oslo hotels are more affected by Airbnb. Stavanger is the city with the largest share of business travelers over the period. However, it has had a large decline in this share since the introduction of Airbnb. The high hotel prices paired with a large decline in business travelers to Stavanger could explain the relatively large market share of Airbnb in Stavanger, and further contribute to Stavanger hotels being more affected by Airbnb than Trondheim.

6. Discussion

In this chapter, I will discuss my results in relation to the relevant literature.

My study joins Zervas *et al.* (2016), Jordet and Lehne (2016) and Farronato and Fradkin (2016) in providing evidence that Airbnb has a quantifiable negative impact on local hotel revenue. Our main findings are consistent in sign and magnitude. However, there are some differences in our estimations.

One obvious difference between my study and that of Zervas *et al.* is the fact that theirs was estimated on data from Texas, while mine was estimated on Norwegian data. Because Airbnb presence is significantly larger in Texas than in Norway, the difference between Zervas *et al.*'s and my estimates are consistent with my results showing that the effect of Airbnb on hotel revenues increase as Airbnb supply increases. My results might have been more comparable with those of Zervas *et al.* if my study had been conducted at a later stage, when Airbnb presence in Norway is more comparable to the Texas presence.

There are some essential differences in my model from that of Jordet and Lehne. Most importantly, I am including the additional control variables *logRoom* and *logAirplanePassengers* to my model. When not controlling for these factors, my coefficient estimate of the effect of Airbnb on hotel revenue increases to -0.0376, closer to Jordet and Lehne's estimate of -0.4. In other words, Jordet and Lehne's estimates might be biased in a negative direction, because they are not properly controlling for changes in tourism demand between cities and changes in each hotel's own capacity.

Furthermore, my identification strategy is based on the possibility of comparing hotel revenues of the same hotels before and after Airbnb introduction. It is therefore essential to my estimation that I have a considerable number of observations before and after this introduction. My data set contains monthly observations in hotel revenue for four years before Airbnb introduction to Norway, and for five years after. The studies of Zervas *et al.* and Jordet and Lehne have obtained data on a longer time period, in particular before Airbnb introduction. I estimate a somewhat smaller effect of Airbnb on hotel revenue than both these previous studies. The fact that I analyze a shorter time period before Airbnb introduction, and observe fewer hotels, might have prevented me from capturing the whole effect.

The difficulty of measuring the right Airbnb supply can also introduce a possible bias to my estimates. First of all, using a cumulative measure might overstate the Airbnb supply over time. If this is the case, my estimates will have a positive bias, because in reality it takes fewer Airbnb listings to affect hotel revenue. Because Zervas *et al.* and Jordet and Lehne attempt to circumvent this problem using alternative Airbnb supply measurement methods, this could explain why my estimates are less negative. Another disadvantage of the cumulative measure is that it does not capture the fact that Airbnb's impact on hotel revenue varies significantly over time, depending on high and low demand periods (see Zervas *et al.* (2016) and Farronato and Fradkin (2016)). Because I am using only a cumulative measure, I have not captured this possibly important effect in my estimates. The fact that the estimations are volatile to the measurement method of Airbnb supply is an obvious weakness of all empirical studies done on the economic effect of Airbnb.

7. Conclusions and economic significance

I estimate through my analysis that a 10 % increase in the supply of Airbnb is associated with a 0.307 % decrease in hotel revenue. Furthermore, when allowing a non-constant elasticity of Airbnb supply on hotel revenue, I found that if Airbnb supply is of over 1000 listings, a 10 % increase in Airbnb supply is associated with a 0.815 % decrease in hotel revenue. In order to understand the magnitude of this impact, it is helpful to look at the effect in terms of Airbnb growth. From 2014 to 2015, Airbnb supply in Oslo, the Norwegian city with the highest presence of Airbnb, grew from 2204 listings in 2010 to 3555 listings in 2015. This means that the estimated impact of Airbnb in Oslo the last year was around 3.8 % of hotel revenue[51].

To put the result in context, I can compare this effect to the estimated effect of an increase in hotel supply, which is that a 10 % increase in hotel supply is associated with a 7.36 % decrease in hotel revenue. This estimate indicates that an increase in hotel supply has a much larger impact on hotel revenue than an increase in Airbnb supply. Consequently, an Airbnb listing is a not a very close substitute to a hotel room. However, Airbnb supply considerably outgrows hotel supply. From 2014 to March 2015, total hotel supply in Oslo grew from 11695 to 12374 rooms. This means that the estimated impact of Airbnb in Oslo the last year was around 4 % of hotel revenue[52]. In other words, even though a 1 % increase in Airbnb has a smaller impact on hotel revenue than a 1 % increase in hotel supply, the strong growth in Airbnb supply compensated for this difference. Even though several analysts have pointed to the increase in total hotel capacity as an explanation for the stagnation in prices and profitability in the largest cities (see, for example, Horwath (2016)), the increase in Airbnb has in fact had more or less the same impact on hotel revenues from 2014 to 2015 as the increase in hotel supply.

I find that the impact of Airbnb on the hotel industry has materialized primarily in a decrease in prices, and only negligibly in a decrease in occupancy rates. According to my estimates, a 10 % increase in Airbnb supply accounts for a 0.27 % decrease in hotel prices. These results are consistent with the results of Farronato and Fradkin (2016), and supports the hypothesis that a sharp increase in tourism to Norway can explain why hotels claim they are not affected

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[51] $1-\left(\frac{3555}{2204}\right)^{-0{,}0815}=0{,}038$

[52] $1-\left(\frac{12374}{11695}\right)^{-0{,}736}=0{,}04$

by competition from Airbnb. Following Farronato and Fradkin, capacity constraints lead the hotels to respond to Airbnb by decreasing prices rather than occupancy rates.

Further, I find that low- and medium price hotels are more vulnerable to competition from Airbnb than high-price hotels. This result supports the hypothesis that Airbnb is a closer substitute to low-price hotels than high-price ones, possibly because the average Airbnb costumer is relatively young and thus has a lower income (Airbnb, 2016). Even though I do not find significant evidence that hotels with a focus on leisure travelers were more affected than business hotels, my results indicate that hotels located in a city characterized by a relatively large share of leisure travelers are more affected by an increase in Airbnb supply. This finding indicates that if Airbnb becomes more popular amongst Norwegian business travelers in the future, the effect of Airbnb on hotel revenue might increase.

Like Zervas *et al.* (2016), Jordet and Lehne (2016) and Faranato and Fradkin, I provide further evidence that Airbnb provides a differentiated product that is not a perfect substitute to hotel rooms, and thus contributes to a larger product variety in accommodation services. Nonetheless, my results also show that Airbnb contribute to lower prices, not only by offering a less expensive alternative, but also by driving down hotel prices. This is consistent with the research of Fraiberger and Sundararajan (2016) and Farronato and Fradkin (2016), which indicate that the introduction of P2P platforms can lead to a higher consumer surplus.

My research contributes to the discussion on the regulation of the sharing economy. The result that Airbnb to a certain degree competes with hotels for the same guests, stresses the importance of regulating each market so that traditional firms and P2P sharing platforms are competing on more equal terms. However, my results also highlight the importance of facilitating P2P sharing, because of the potential benefits these alternatives have on competition and ultimately on consumer welfare. Regulating each Airbnb host like a hotel will diminish the efficiencies related to P2P sharing, limiting the benefits of the sharing economy. The key might be to adapt existing market regulations to the “information society”, possibly focusing more on data transparency and accountability than on bureaucracy and permission-based systems. The results from my empirical analysis, paired with the fast growing number of P2P platforms and the increasing interest of the Norwegian people in taking part in the sharing economy, indicate that P2P sharing platforms will have an increasing effect on existing markets in Norway in the years to come.

8. Topics for further research

Much of the existing literature on the effect of Airbnb has estimated a significant, negative effect of Airbnb on the peak pricing power of hotels. These studies indicate that this effect is possibly one of the most important effects of P2P platforms on traditional firms, stemming from P2P sharing platforms having the advantage of offering a more elastic supply (Zervas *et al.* (2016) and Farronato and Fradkin, (2016)). Studying this effect in Norway could be interesting, considering the large variations in capacity constraints facing the hotel markets in Norwegian cities depending on the season. It could for example be possible to look at the effect of Airbnb on hotel pricing power during Nor Shipping, a shipping conference held every other year in Oslo, which each time results in all hotel rooms in Oslo being fully booked months in advance.

Another interesting research subject is the degree of professionalization of P2P sharing platforms like Airbnb. If hotels and similar establishments are increasingly using P2P sharing platforms as a supplement to their own sales channels, this increases the importance of regulating P2P platforms and hotels similarly, and affects the possibility of P2P sharing platforms increasing consumer welfare.

Not only is the short term accommodation market facing the advancement of P2P accommodation sharing platforms. There has also been increasing interest in these platforms' impact on the housing market. In several cities, Airbnb is being blamed for increasing prices in the long term accommodation rental market, as landlords prefer renting out their apartment short term to Airbnb guests than long term to locals[53]. Housing prices might also increase, if Airbnb rental is so profitable that an increasing amount of people buy apartments with the intent of renting them out through Airbnb. An analysis on the effect of Airbnb on the long term housing market would be a welcome contribution to this debate.

[53] http://e24.no/digital/delingsoekonomi/bekymret-for-airbnb-og-boligmarkedet-kan-ikke-komme-med-en-ny-plattform-og-tro-at-man-ikke-er-regulert/23816377 [Read 16.10.2016]

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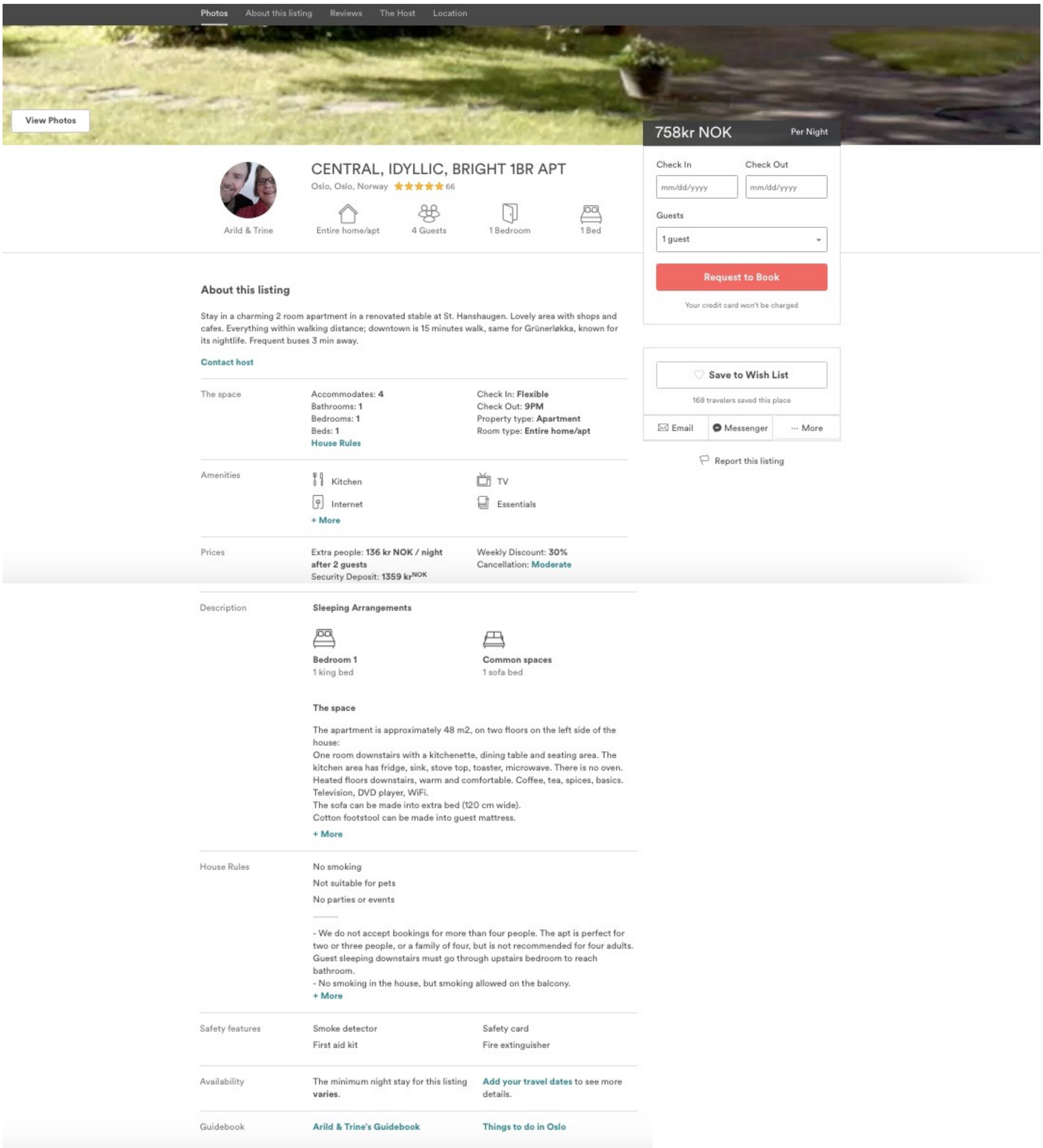
Appendix

A.1 Figures

Figure A1: Typical example of an Airbnb listing[54]



[54] https://www.airbnb.com/rooms/921279

Figure A2: Airbnb guests stays in Norway, 2015

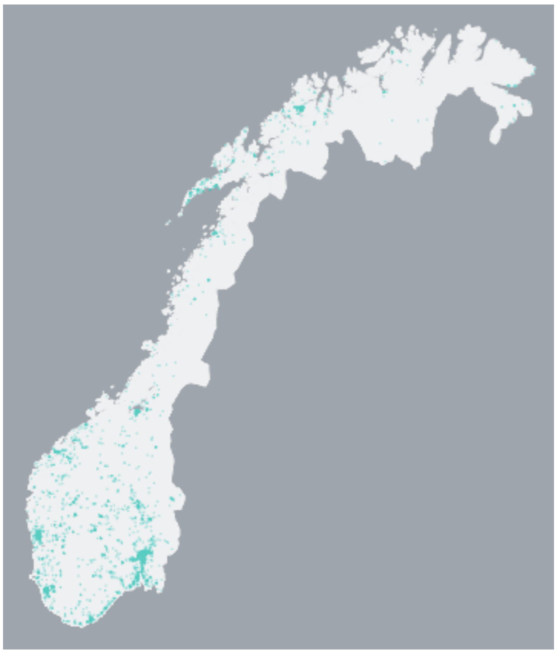
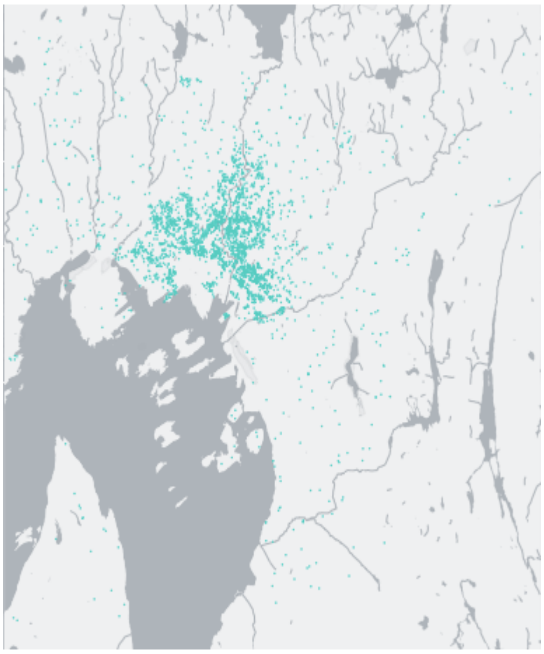


Figure A3: Airbnb guest stays in Oslo, 2015



Source: Airbnb

Figure A4: Number of Norwegian Airbnb hosts, 2015. Source: Aftenposten

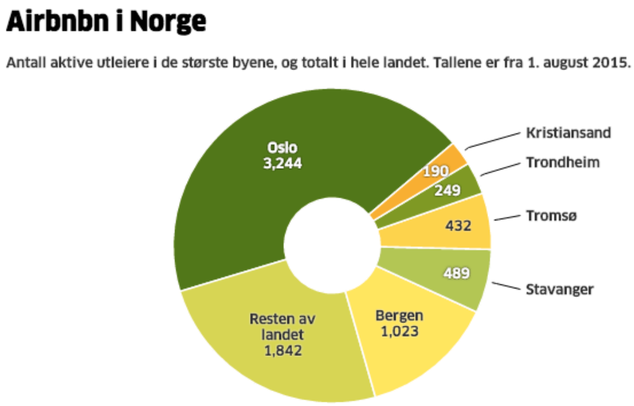
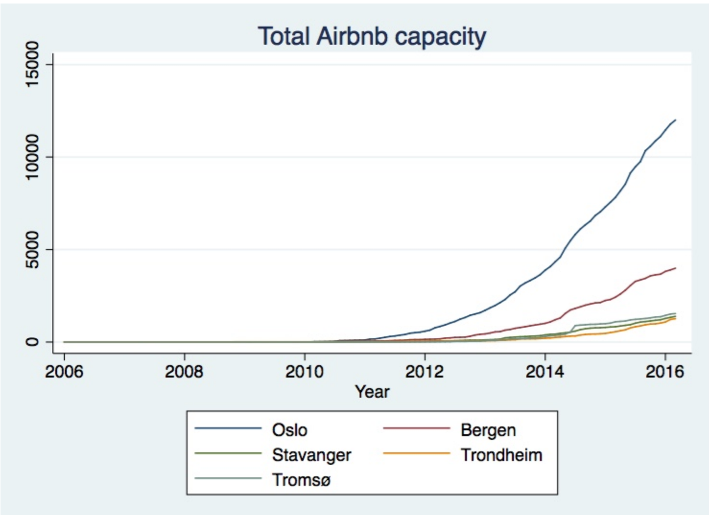


Figure A5: Total Airbnb capacity, by city



A.2 Tables

Table A1: Alternative measure of Airbnb supply

VARIABLES	(1) Nb of listings	(2) Capacity	(3) Market share
logairbnb	-0.0307***	0.0188***	0.351
	(0.00353)	(0.00346)	(0.356)
logHotelSupply	-0.737***	-0.756***	-0.767***
	(0.0560)	(0.0628)	(0.0588)
logrom	0.761***	0.762***	0.762***
	(0.116)	(0.116)	(0.117)
logpop	0.0537**	0.0666***	-0.0144
	(0.0153)	(0.0143)	(0.0266)
Ledighet_andel	-0.0819***	-0.0845***	-0.0857**
	(0.0154)	(0.0154)	(0.0212)
logpasstot	0.903**	0.932**	0.931**
	(0.263)	(0.245)	(0.253)
Observations	18,118	18,118	18,118
R-squared	0.417	0.416	0.416
Number of lopenr	202	202	202

All specifications include hotel, city and time fixed effects, and a city-specific, linear time trend
Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2: Alternative log of Airbnb supply

VARIABLES	(1) FE(original)	(2) FE(alternative)
logAirbnb	-0.0307***	-0.0301***
	(0.00353)	(0.00414)
logHotelSupply	-0.737***	-0.742***
	(0.0560)	(0.0591)
logRoom	0.761***	0.761***
	(0.116)	(0.116)
logPopulation	0.0537**	0.0280
	(0.0153)	(0.0195)
Unemployment	-0.0819***	-0.0819***
	(0.0154)	(0.0155)
logAirplanePassengers	0.903**	0.902**
	(0.263)	(0.255)
Observations	18,118	18,118
R-squared	0.417	0.417
Number of hotels	202	202

All specifications include hotel, city and time fixed effects, and a city-specific, linear time trend
Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A3: Quadratic Airbnb supply

VARIABLES	(1) FE
logairbnb	-0.0220***
	(0.00364)
$logairbnb^2$	-0.00307
	(0.00164)
logHotelSupply	-0.737***
	(0.0616)
logrom	0.761***
	(0.116)
logpop	0.0573**
	(0.0167)
unemployment	-0.0824***
	(0.0160)
logpasstot	0.877**
	(0.273)
Observations	18,118
R-squared	0.417
Number of hotels	202

All specifications include hotel, city and time fixed effects, and a city-specific, linear time trend
Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A4: Lags of Airbnb supply

VARIABLES	(1) No lag	(2) 1 month lag	(3) 2 month lag	(4) 3 month lag	(5) 6 month lag
logAirbnb	-0.0307***				
	(0.00353)				
$logAirbnb_{-1}$		-0.0271***			
		(0.00478)			
$logAirbnb_{-2}$			-0.0313***		
			(0.00571)		
$logAirbnb_{-3}$				-0.0315***	
				(0.00506)	
$logAirbnb_{-6}$					
					-0.0260**
					(0.00821)
logHotelSupply	-0.737***	-0.724***	-0.719***	-0.700***	-0.674***
	(0.0560)	(0.0510)	(0.0605)	(0.0618)	(0.0639)
logRoom	0.761***	0.754***	0.758***	0.763***	0.768***
	(0.116)	(0.124)	(0.124)	(0.124)	(0.130)
logPopulation	0.0537**	0.0496***	0.0681***	0.0722***	0.0897**
	(0.0153)	(0.0104)	(0.00855)	(0.0114)	(0.0235)
Unemployment	-0.0819***	-0.0842***	-0.0832***	-0.0826***	-0.0853***
	(0.0154)	(0.0151)	(0.0138)	(0.0138)	(0.0135)
logAirplanePassengers	0.903**	0.888**	0.866**	0.886**	0.874**
	(0.263)	(0.260)	(0.268)	(0.272)	(0.277)
Observations	18,118	17,916	17,718	17,523	16,952
R-squared	0.417	0.420	0.419	0.421	0.425
Number of hotels	202	198	195	191	190

All specifications include hotel, city and time fixed effects, and a city-specific, linear time trend
Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A5: Variation of impact across cities

VARIABLES	(1) Revenue	(2) Prices
logAirbnb	-0.0162	-0.00635
	(0.0110)	(0.0103)
Oslo ×logAirbnb	-0.0220*	-0.0282**
	(0.00899)	(0.00900)
Stavanger ×logAirbnb	-0.0275*	-0.0349**
	(0.0121)	(0.0121)
Bergen ×logAirbnb	-0.000110	-0.00518
	(0.0109)	(0.0109)
Tromsø ×logAirbnb	-0.00875	-0.0154
	(0.00973)	(0.00920)
logHotelSupply	-0.701***	-0.680***
	(0.0540)	(0.0550)
logRoom	0.762***	-0.261*
	(0.116)	(0.107)
logPopulation	0.0427**	0.0287**
	(0.00951)	(0.00917)
Unemployment	-0.0788**	-0.0821**
	(0.0223)	(0.0239)
logAirplanePassengers	0.911**	0.944**
	(0.296)	(0.310)
Observations	18,118	18,118
R-squared	0.417	0.357
Number of hotels	202	202

All specifications include hotel, city and time fixed effects, and a city-specific, linear time trend
Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1