Aalto University
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INDIVIDUALS' CAPABILITIES IN PRICING THEIR OFFERING IN COMMERCIAL SHARING SYSTEMS

Analysis of Airbnb accommodation prices

Master's Thesis
Petri Aalto-Setälä
Aalto University School of Business
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Aalto University
School of Business
Aalto University, P.O. BOX 11000, 00076 AALTO
www.aalto.fi

Abstract of master's thesis

Author Petri Aalto-Setälä

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Abstract

This study seeks to shed light on the capability and preparedness of individual sharing economy users to price their offering and adjust the pricing based on changes in demand. Central to the topic are the concepts of revenue management, yield pricing and price determinants identified in hotel industry and Airbnb price determination. The chosen research approach is to use statistical data analysis based on open source data from Insideairbnb.com and Trivago hotel price indices. This allows for drawing conclusions based on host pricing behavior during 2015-2017 in five Europeans cities, five North American cities and two Australian cities. All twelve are major cities with thousands of Airbnb listings available each month. Previous research has not sought to examine pricing in sharing economies in this way.

Previous research has identified that user characteristics influence participation in sharing economy and findings in the empirical section of this study would suggest that a majority of users do not actively pursue higher profits through revenue management that is comparable with the hotel industry in magnitude. Additionally, this study showed that due to the different nature of rented space on Airbnb to hotels, prices may be cheaper closer to the actual stay rather than several months beforehand. This study does not suggest that Airbnb hosts should pursue higher profits and do business with their apartments. Hosts should be aware of the limitations that regulation sets on their rentals and applicable taxation practices.

Should future business models be dependent on individuals pricing their own offering, based on the findings in this study, considerations should be made not only from the view of the viability of the business for the individual and platform provider, but also the regulatory point of view to avoid unleveled playing fields and predatory pricing.

Keywords sharing economy, revenue management, dynamic pricing, Airbnb, hotel industry, business model, predatory pricing, price determinants, price evolution

Aalto-yliopisto, P.O. BOX 11000, 00076 AALTO
www.aalto.fi

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Tiivistelmä

Tämän tutkimuksen tarkoituksena on tarkastella yksityishenkilöiden kyvykkyyksiä ja valmiuksia hinnoitella tarjontaansa jakamistaloudessa. Hinnoittelua tarkastellaan muutoksissa hinnoissa huomioiden kysynnän vaihtelu vuoden aikana. Keskeisiä konsepteja tutkimukselle ovat tuoton hallinta (revenue management), katehinnoittelu sekä hotellien ja Airbnb hinnan määrittävät hintatekijät. Tutkimus toteutetaan tilastollisella data analyysillä. Datalähteinä toimivat Trivagon kuukausikohtaiset hintaindeksit sekä Insideairbnb.comin tuottama avoin data tutkimuskäyttöön. Nämä tietolähteet mahdollistavat Airbnb hintojen tarkastelun aikavälillä 2015-2017 ja otokseen kuuluu yhteensä 12 kaupunkia (viisi Euroopasta, viisi Pohjois-Amerikasta sekä kaksi Australiasta). Kaikissa kaupungeissa on kuukausittain useita tuhansia asuntoja/huoneita tarjolla.

Aiempi tutkimus aiheesta on tunnistanut käyttäjän luonteenpiirteiden ja käsityksien vaikuttavan halukkuuteen osallistua jakamistalouteen. Aiempi tutkimus ei ole pyrkinyt tutkimaan jakamistalouden hinnoittelua ehdottamallani tavalla. Empiirisen osion havaintojen pohjalta suurin osa Airbnb:ssä vuokraavista ihmisistä ei pyri korkeampaan tuottoon muokkaamalla hinnoitteluaan kysyntäpiikkien mukaan – ainakaan hotelleihin verrattavissa olevassa skaalassa. Tutkimus näytti, että Airbnb:n ja hotellien eriävästä luonteesta johtuen, Airbnb-asunnon hinta voi olla halvempi lähempänä matkustuspäivää kuin kuukausia aikaisemmin. Tutkimuksen tarkoitus ei ole ehdottaa, että Airbnb-isäntien tulisi pyrkiä korkeampaan tuottoon ja tehdä liiketoimintaa asunnollaan. Airbnb:ssä vuokraavien tulisi tiedostaa lain asettamat rajoitteet lyhytaikaiselle vuokraamiselle sekä soveltuvat verosäädökset.

Tutkimuksen havainnot ovat tärkeitä, mikäli tulevaisuuden liiketoimintamallit ovat riippuvaisia yksityishenkilöiden kyvykkyydestä hinnoitella tarjoamansa. Harkintaa tulisi tällöin osoittaa sekä yksityishenkilön että alustantarjoajan osalta. Samalla lainsäädännön näkökulmaa ei tule unohtaa, jotta markkinatoimijat toimivat samoilla edellytyksillä eivätkä syyllisty saalistushinnoitteluun.

Avainsanat jakamistalous, tuotonhallinta, dynaaminen hinnoittelu, Airbnb, hotellitoimiala, liiketoimintamalli, saalistushinnoittelu, hintatekijät, hinnankehitys

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1 Introduction

1.1 Background and motivation

The concept of sharing economy has received much interest in the past years. It continues to gather new business ideas and aspiring market disruptors today. Estimates of the future market potential predict a growth from $15 billion to $335 billion in 2025 in P2P finance, online staffing, P2P accommodation, car sharing and music/video streaming (PwC, 2014). Most people can easily recognize widespread brands such as Airbnb, Lyft, Uber and in Helsinki the well-received city bikes, DriveNow and maybe even OP Kulku. Each service is different in their own ways, in terms of pricing and subscriptions. Some classifications of sharing economies exclude certain services based on their business model, while archaic versions of sharing economies also exist – such as libraries.

The primary interest in the subject field lies with yield management or revenue management that a sharing economy based business model employs – an approach that is not exclusive to sharing economy. More specifically, I am interested in examining the capability of individual citizens in determining the right market price for the product/service/accommodation that they are providing. If future business models rely more on consumers setting the price for services and products, corporations would have a major incentive to guide them in setting the rental price as close to valid market price as possible. In the case of Airbnb or Uber for example, the companies receive their profits by receiving a percentage of what the customer pays for their stay or taxi ride. From here onwards the business models differ, as Uber sets the prices that the drivers must accept while Airbnb makes no pricing decisions on the users' behalf and try to underline this distinction to the authorities.

In this thesis, I will focus on Airbnb and the way that their hosts set prices for the accommodation that they provide. I will draw parallels between the disrupting player and traditional hotel industry to examine to what extent the average Airbnb price differs from hotel prices each month. Airbnb has launched initiatives to educate the hosts to set their rental prices according to their suggestions. They provide insights to aid hosts in selecting the suitable price through their proprietary algorithms (Airbnb, 2015). Airbnb’s default capabilities for price setting have been criticized (Airbnb Community Center, 2016-2017), and external service providers have risen to help Airbnb hosts maximize their profits such as Beyond Pricing and Guesty.

The hotel industry along with the airline industry have embraced the practice of yield management (a form of revenue management) a long time ago to maximize their profits with their limited capacity to accommodate guests. I will examine the different tactics to maximize revenue employed by the hotel industry, and examine these tactics in the case of Airbnb where pricing decisions are left with the citizens renting their apartments and rooms to complete strangers. However, I will deliver my main contribution through data analysis, which examines several locations on a high level, instead of focusing the pricing tactics of single Airbnb hosts.

Business models with a sharing economy approach at heart have entered several markets – and one could argue have been on the market for a long time. People's reasons to participate in sharing economy is a factor that could be expected to affect their pricing behavior – a point that merits further examination through the literature review. Nevertheless, not considering for varying motivation in engaging in sharing economy, people seek to set a price that gives them a reasonable return on their offering. Do they have all the necessary information to set the price correctly, however, and the question remains – do they price their offering the way they should?

1.2 Objectives

My thesis aims to shed light on the ability (and willingness) of individual citizens to perform pricing decisions. I.e. price their rental offering on par with the market price, and expand the finding to provide suggestions for businesses seeking to use sharing economy based business models in general – not only for Airbnb or the lodging industry.

Upon reading this thesis the reader will be familiarized with concepts of revenue management, different price determinants in the hotel industry, price determinants in Airbnb and be able to identify the importance of providing individual citizens (freelancers) with tools that facilitate pricing decisions. The literature review section will highlight the importance of transparency in pricing models.

Key contribution from the thesis will be, however, the increase in knowledge of how prepared Airbnb hosts – and by extension individuals in general – are to take responsibility of pricing their offerings. If business models where companies allow their freelancers (individual citizens) decide the prices for them become more common in the future, they will have to be careful with how they do it and should they do it. These objectives translate into the following research questions detailed in the next section.

1.3 Research questions

1) What can be discerned from identifiable trends between Airbnb pricing and hotel pricing?

2) Based on Airbnb rental booking and price data, how common is it for hosts to perform revenue management?

3) What differences can be discerned from host pricing practices, and how does it relate to previous research into sharing willingness?

1.4 Theoretical and practical contribution

Previous research has examined consumers' willingness to participate in sharing, and sought to classify users based on that willingness. Previous research seems not to have examined revenue management from the point of view of sharing economy businesses, which provides a research gap for theoretical contribution. This thesis pursues to examine sharing economy revenue management quantitatively. This approach facilitates examining revenue management maturity in different geographical locations and different cultures.

Practical contributions look to provide recommendations for business managers and future entrepreneurs that may look to use a sharing economy business model as basis for their service. Especially integral for them will be the conclusions of possible pitfalls in facilitating consumer-dependent revenue management.

1.5 Structure of the thesis

This thesis will consist of the three parts. In chapter two I will dive into the current academic literature on the topic including: yield management, pricing schemes, definitions of sharing economy and more. In the following chapter I will discuss the methodology employed in approaching Airbnb data, Hotel prices and data limitations. After this I will present my findings from the data and engage in discussion of what the implications are and avenues for future inquiry based on the findings and my written analysis. Finally, in the fifth chapter I will present the concluding thoughts of this study.

2 Literature review

The purpose of this section is to discuss previous research on relevant topics, draw parallels between 'traditional' and disruptive business models and provide a framework with which to approach the empirical section of this thesis. Sections in the literature review are divided according to topic, yet are integrally related to each other to build a frame through which my empirical contribution can be understood.

2.1 Definitions of sharing economy

2.1.1 Differences in terminology

Sharing economy as a concept started to gain identification in the 2000s (Richardson, 2015). However, sharing itself is as old as humankind itself (Belk, 2014). As Richardson describes it, sharing economy is usually characterized as a form of exchange that takes place through an online platform. Huefner (2015) describes sharing economy as something that focuses on access to specific resources rather than having direct ownership or control of the resource. Other terms used to describe the same phenomenon include collaborative economy (Richardson, 2015), collaborative consumption (Botsman & Rogers, 2010) and commercial sharing systems (Lamberton & Rose, 2012; Akbar et al, 2016) when referring to the platform or ecosystem. Sharing economy and collaborative consumption are terms born in the Internet age and are terms used sometimes interchangeably. (Belk, 2014.) Belk pursued to distinguish the fine differences of sharing and lending. When you help a stranger by telling them the time of day or point them towards the train station, are you actually sharing something? Belk also mentions the often used 'borrow' as a euphemism for sharing (i.e. can I borrow a piece of paper.)

Both Richardson's (2015) and Belk's (2014) descriptions of collaborative consumption encompass both non-profit and for-profit activities. Another description by Stephany (2015) brands sharing economy to pursue taking advantage of under-utilized assets and making them available online. These two descriptions converge in the sense that they both require an online market place to enable the subsequent transactions to take place. Belk discusses the online sharing of media (films, TV shows, games, music etc.), which in some cases is legal or illegal. For practical purposes it is safe to assume that illegal business activities are not included in the desired definition of sharing economy.

Lamberton & Rose (2012) make a distinction between open and closed commercial sharing systems (CSS). In an open CSS a shared good is available to all consumers in exchange of a compensation. However, in a closed CSS the restricted group is allowed access to the shared resource. This restriction stems from membership, relationship, etc. Akbar et al. (2016) posit that if a consumer is materialistic and possessive of goods, their participation in commercial sharing systems is restricted, but not entirely dependent on other characteristics of the consumer and specific resource.

Collaborative consumption is a form of consumption in which people coordinate their use (Belk, 2014). However, a focus on the "joint" activity is not enough, as simply doing something together is not enough. Belk dismisses definitions that are more depictive of traditional sharing or lending, and determines the exchange of a fee or compensation to be necessary in the definition. Belk recognizes a difficulty in the popular car "sharing" enterprises such as Zipcar.com (or DriveNow in Finland), which may call themselves as commercial sharing ventures, but Belk defines them as pseudo-sharing and as short-term rentals. Other academic literature has also highlighted the difficulty in defining the boundaries of rentals and sharing economy. Modern car rentals can take place through an online website or platform, which would constitute an element described by Richardson (2015) i.e. it uses an online platform as marketplace for the transaction. However, using the definitions of Belk (2014) and Richardson (2015), a car rental business doing short-term rentals through an online platform would not be a "true" sharing economy business.

Richardson (2015) posits the problem with 'sharing' part of the term: what constitutes as sharing and what does sharing promise for the economy. Richardson discusses the implication of sharing economy in the perspective of work-sharing and links the concept with terms such as gig, on-demand or crowd-sourcing economy. Sharing economy seems similar to crowd-sourcing economy in it that they both use in the company's point of view external resources to reach their objectives. Richardson identifies that academic literature has identified the connection between sharing economy and its relation to changes in consumption. She identifies three elements of sharing economy in Airbnb: 1) an online platform as a marketplace, 2) transactions are peer-to-peer, 3) the service is access-based. The first element provides cost-reduction as prices go down as supply and demand grow. However, as Richardson points out, the latter two elements are not definitely set in all definitions present in academic literature. An access-based service would exclude services, which transfer ownership of a resource or service instead of just temporary access. On pure face value, this constitutes a better definition of "sharing" than with an exchange of ownership. A service where ownership changes had in quick succession could be better classified as circular economy, where the focus is placed on the full lifecycle of a resource depending on further characteristics of the lifecycle.

Belk (2014) and Richardson (2015) seem aligned in their definition that a rental firm, which does not enable peer-to-peer transactions, does not constitute a sharing economy business. Belk recognizes, however, that several car manufacturers have launched new business models, where consumers share the cars they use. The sharing is done either through the short-term rental mentioned before or through carpooling, which sounds more extensively a shared activity. Belk provides a reasoning for the companies to be doing these new business models, which erode their traditional business models. Instead of fighting the disruptive market changes, the companies have opted to embrace the disruption instead of the options flight-or-fight, which worked less than optimally for the film, music and publishing industries. As Huefner (2015) points out, traditional companies can remain viable and maintain their coverage if they adapt to the new circumstances. He predicts that peer-to-peer sharing can become another way for traditional companies to provide their goods and services to their customers.

The peer-to-peer element of sharing economy can be switched (Richardson, 2015). Therefore, as she points out the host can guest can easily swap places and the community of sharing economy requires a level of receptiveness in encountering strangers visiting your home. This creates a requirement for trust that requires structure built within the platform. Different ratings and safeguards help improve the performance and build trust in the platform (e.g. Richardson, 2015; McAfee & Brynjolfsson, 2016)

Richardson discusses the way collaboration in the sharing economy plays a part, and more accurately the co-operation through sheer labor. This would imply that sharing a workforce would constitute a part of sharing economy. Crowdsourced labor could be characterized as the modern day freelancing, which, as Richardson points out as possible critique, acts as a way to splinter the workplace. Companies such as Uber benefit from the commissions they receive from their drivers, but reduce their own risk by not having to treat their drivers as employees and do not follow the regulations involved if they were.

2.1.2 Criticism of sharing economy as a concept

Sharing economy has been branded as duplicitous (Richardson, 2015; Martin, 2016) and is considered at the same time a part of the capitalist economy and an alternative to it (Morozov, 2013). Botsman & Rogers (2010) have suggested that sharing economy can act as a balancing force on the forces that drive hyperconsumption in modern capitalism. Morozov (2013) posits that while sharing economy businesses maintain that the business concept is something that benefits everyone, another possible view is that sharing economy is a utopia, which in fact limits worker rights by reducing employees to freelancers. Sharing economy businesses have run into issues with existing market players looking to prevent their market entry and growth (e.g. Cusumano, 2015; Belk, 2014).

Belk (2014) and Richardson (2015) have noted in their work that businesses have used the terms sharing economy, collaborative consumption or car sharing to describe their enterprises, while their business activities seem more like renting and outsourcing of work rather than "true sharing". Further criticism has been placed on the way sharing economies actually affect consumption. Researches have pointed out the moral hazard similar to agency theory in sharing economy (Cohen & Kietzmann, 2014). Cohen and Kietzmann posit that the private sector has developed business models in order to address a market failure to deliver sufficient service level for consumers.

Cusumano (2015) details his view on actions traditional companies should enact when dealing with disruptive sharing economy ventures. His view can be best described as the "fight" approach to market entrants. Cusumano details the pitfalls that Airbnb and Uber have built into their business models, when considering present day regulations and legal requirements. He directs companies to pursue balanced treatment through checks for violations in taxation, insurance policies, licensing issues etc. Cusumano mentions the court case from Germany, where Uber received a nationwide ban on its operation. The aforementioned actions are ways to make sure the playing field is the same for both types of companies – traditional and sharing economy businesses. However, regulations have been drafted with the current market players in mind, and as sharing economy defenders would argue, should not apply to sharing economy businesses.

Cohen and Kietzmann (2014) discuss sharing economy from the point of view new mobility solutions. As mentioned earlier, their view is that new mobility solutions are meant to address a prevalent market failure, which causes congestion and time wasted moving from one place to another. At core of the mobility solutions is to achieve a sustainable way of commuting.

If Botsman & Rogers (2010) considered sharing economy as an alternative to hyperconsumerism, Morozov (2013) dubbed sharing economy as ‘neoliberalism on steroids’. Morozov’s point of view seems to be that in a sharing economy, workers’ rights deteriorate from what has been a status quo for the past decades and a delicate balance of rights and requirements between the employer and employee. In a sharing economy business model the self-employed entrepreneurs are not entitled into healthcare paid by the company, insurance benefits and bear the economic risk of an entrepreneur: business does not run while you are sick (Morozov, 2013).

Aside from workers’ rights, the greenwashing-like touch in the discussion can be understood over the effects on consumerism. As pointed out by some researches a sharing economy business model in itself is not sustainable unless certain conditions are met. If the business model makes a resource more accessible through sharing, it most likely increases the use of said resource and if using that resource has an environmental effect, then sharing increases environmental strain (e.g. Scheepens et al., 2016). Through car sharing a person may use a car more than that person would be able to drive without owning one. Therefore, the environmental effect is larger than it would have been had the person taken the bus instead. The underlying cause for this conclusion according to Scheepens et al. (2016) is the ‘rebound effect’, which constitutes that when people save money due to some technological change for example, they spend that money on something else. The point made by Scheepens et al. (2016) is that if the new resource that is shared is either more environmentally friendly or is used more sustainably, then the sharing economy business model is truly beneficial for increasing sustainability.

Sharing economy solutions can reduce the number of resources used, however. Take the previous example of car sharing: if ten people can use one car consecutively instead of buying ten cars, fewer resources go into manufacturing and transporting one car to the same part of the city instead of manufacturing and transporting ten cars. In this example, the total demand for cars is lower as people have the chance to share cars. Similar findings have been made in academic literature (e.g. Huefner, 2015). Huefner highlighted the future promise available through the development of driverless technology, which can open new avenues of boosting the sharing economy.

2.2 Sharing economy business models

2.2.1 User dependent view

Sharing economy business models are heavily dependent on the needs of the consumers on that market (Lamberton & Rose, 2012). Hellwig et al. (2015) identified four clusters of customers in the perspective of sharing economy. These clusters have varying opinions about sharing, willingness to share and reasons for doing so. Sharing opponents are found to be the second biggest group at 28%, which can be expected to include some materialistic consumers discussed in research by Akbar et al. (2016). Research by Hellwig et al. (2015) indicated that sharing opponents lacked motivation to participate in sharing economy business models. The challenge in light of Akbar et al. (2016) and Hellwig et al. (2015) is thus to identify product categories that sharing opponents most associate with resource scarcity and offer them suitable unique products. Akbar et al. (2016) posit that the offer of unique products can be enough to counter the sharing opponents' lack of sharing motivation. This could be understood as caused by the limiting effect on consumption by the business model, which the researchers deem it to be. However, Akbar et al. (2016) identify that a need for unique consumer products increases the willingness to participate in a CSS, when they do not possess that product or a product of that category. This shared resource specific view is discussed further in the section 2.2.2.

Hellwig et al. (2015) detail their view on how to build sharing economy business models to be successful in appealing to different clusters of users. As mentioned before, sharing opponents can be difficult consumers to include in the business due to their aversion to sharing, yet is not impossible. The researchers have identified the key motivating drivers for the other user clusters, however. Essential difference between the groups is answered through the question on why they participate in sharing. Sharing idealists as a group consider sharing as natural and enjoy the social and emotional benefits associated with it. In contrast sharing pragmatists participate for the convenience and utility that sharing provides them. This can be understood as having access to resources that otherwise would be out of their price range, is too expensive to own or is impractical to own instead of sharing it with others.

Sharing pragmatists can be seen as being close to sharing idealists in it that they both see it as something natural to do, and can be one reason why sharing pragmatists do not feel it necessary to demonstrate their ethical and responsible behavior purely for the image value. In contrast, the normative sharers look for opportunities to signal their effort to protect the environment and tackle excessive purchasing over sharing resources with others. Normative sharers would be less likely to participate in sharing economy businesses, where the commercial sharing system does not facilitate external signaling or is not otherwise apparent on the outside that the person is participating in sharing economy. Further characteristics of these clusters identified by Hellwig et al. (2015) are detailed in the following table including the respective percentages of the portions of users in the researchers' study.

Table 1: Clusters of CSS user groups, associated characteristics and motivations. Drafted mostly from research by Hellwig et al, 2015 and with addition from Akbar et al, 2016.

Cluster	**%**	**Description of characteristics and motivations**
Sharing Idealists	30,5	Most often female (67.3%) Very sociable on social media Most generous and prone to reciprocity Does not expect tit-for-tat reciprocity Does not consider themselves short of resources **Primary driver:** Integrated motivation. Sharing is a natural thing to do. Emphasize social and emotional benefits. **Least influential driver:** Introjected. Overemphasis on practical utilitarian gain is alienating.
Normative Sharers	30	Evenly men and women Most active on Facebook Generous Prone to tit-for-tat reciprocity Considers themselves short on resources **Primary driver:** Introjected. Sharing is socially desirable. Emphasize signaling value of sharing as ethical and responsible behavior. **Least influential driver:** Integrated. Business models not enabling signaling alienating.
Sharing Opponents	28	More often men (57%) Not present in social media (55% not on Facebook) Not very generous, low motivation for sharing Low resource scarcity **Primary driver:** none Research by Akbar et al. (2016) suggests offering unique products to sharing opponents to bypass their lack of sharing motivation **Least influential driver:** Low sharing motivation across the board.

Sharing Pragmatists	11,5	Most often men (71.3%) Sociable with a rich social environment Low generosity and reciprocity Averagely prone to sharing Mostly white-collar workers with a full-time job **Primary driver: Introjected**. (however low) Sharing is a pragmatic thing to do. Emphasize convenience and utility. **Least influential driver:** Integrated Avoid overemphasis on signaling value of sharing.

Considering the very different potential groups in the above, it would be fair to say that sharing economy business models require a good insight into who their users are and who they are looking to have as customers. Philip et al. (2015) highlight the reasons why people may feel uneasy at joining sharing economies due to the risks of negative reciprocity and even the inflexible design of P2P rental sites. Another barrier that businesses would have to overcome is the desire for owning things (Behrendt et al., 2013). Lamberton & Rose (2012) discuss the possibilities available for managers to create trust with their users and in affecting their perceptions of associated risk factors. However, as they point out, no theoretical framework exists to aid managers' in marketing related challenges. Lamberton & Rose (2012) highlight that by designing parts of their sharing system and marketing communications accordingly, managers can affect the perceived risk of product scarcity. Product scarcity speaks to a user's desire to have access to a product when they want, instead of having to wait.

2.2.2 Shared resource based view

Hellwig et al. (2015) discuss the characteristics of items to be shared through economy as a potential way of determining why certain items are unsuited to be shared. They posit that the more relevant an item is to a person's extended self, the less likely it will be shared. Extended self is characterized that a person unknowingly, intentionally or unintentionally regards a possession a part of themselves (Belk, 1988) and the continuous rise of digital goods and alternative focus points of possession has increased the ways people define their extended selves (Belk, 2013).

Akbar et al. (2016) identify that sharing a resource with a high product-need-fit is best suited for sharing economy purposes. The reason for this is that depending of the product in question, having just one may not be enough. If for example someone lists a screwdriver in a CSS, one specific screwdriver may not work with all of my furniture, therefore a screwdriver or other tools like it have a low product-need-fit. In the point of view of my empirical section, Airbnb apartments fill a specific need for accommodation, yet there are other determinants in selection and price determination when it comes to selecting a place to stay. I will describe these further in sections 2.4 and 2.5.

Scheepens et al. (2016) examine the shared resource with sustainability in mind. However, they note that certain products such as clothing or mobile phones are not especially suitable for shared use. They also make the example of two families needing a car: “when two families have a car and drive 25,000 km per year, and the life span of the car is 250,000 km, they will need two cars per 10 years, regardless whether they share the cars or not” (Scheepens et al., 2016, p.258). From a consumer point of view this example disregards the monetary effect of sharing that car altogether. If both families purchase a car, both pay a large sum at year 0 instead of paying 50% of the car value at year 0 and again 50% at year 5 when they purchase the second car together. Vogtländer et al. (2014) also state that when a sharing economy solution saves the user some money, the subsequent “rebound effect” potentially causes environmentally adverse consumption. Scheepens et al. (2016) consider the characteristics of the shared product as such: “when products save energy in the use phase, but require higher upfront investment (e.g. an electric car), leasing is an important component in the business model.

Scheepens et al. (2016) note that due to the nature of the resource being shared, the sharing users may show less concern about its maintenance, which increases the lifecycle environmental cost and burden. Their consideration is placed on the overall environmental impact, but one could expect this moral hazard to influence the individual leasing their asset for sharing. If the users handle the asset less carefully and with less concern for the cleanliness, the burden of managing the asset falls on the real owner. In line with the thoughts of Scheepens et al. (2016) that items such as clothing or mobile phones and Hellwig et al. (2015) that products part of the extended self are not suited for sharing, it could be a reason of the owner’s understanding and fear of the moral hazard: owners recognize that users may show disregard for a product that they hold dear, and are therefore unwilling to share that extended part of themselves.

Table 2: User propensity to share different categories of items divided by clusters of CSS user groups (using Likert scale 1 = share with nobody, 3 = only with reservations [wuth spouse, family, close friends], 5 = with everyone)

Hellwig et al, 2015

	Mean values (Likert scale 1-5)			
Variable	**Idealists**	**Normatives**	**Pragmatists**	**Opponents**
Practical wisdom	4,40	4,19	4,05	3,97
Nutrition	4,32	4,13	4,00	3,77
Photos and music	4,04	3,81	3,83	3,49
Households	3,44	3,16	3,23	2,83
Personal belongings	3,03	2,78	2,88	2,50
Personal information	2,08	1,91	2,09	1,78
Intimates	1,42	1,35	1,53	1,29

Hellwig et al. (2015) examined in their research the sharing willingness of the user clusters in their research based on the category of shared resource. Their findings indicate that idealists and pragmatists are the similarly likely to share with the idealists more likely to share non-personal resources while pragmatists are more willing to even share personal information about themselves and intimates. The researchers determined 2,5 as the threshold for reserved sharing with others, i.e. sharing willingness under 2,5 is somewhat reserved (on a Likert scale 1-5). For my research in the empirical part, this table provides an interesting contribution as even sharing opponents are not reserved about sharing their households with others, which means that Airbnb users can belong into all four user clusters. However, the sharing opponents are the least likely of the four to share their household with someone.

Constantiou et al. (2017) examined sharing economy business models based on their offering from the perspectives of control and rivalry. The subsequent 2x2 table categorized sharing economy business models into 1) franchisers, 2) chaperones, 3) principals and 4) gardeners. The researchers identify Airbnb users as facing loose control from the platform owners, yet high rivalry. The rivalry mechanism in Airbnb is heightened due to not only competition between other disruptive hospitality platforms, hotel chains and traditional hospitality industry players, but also competition between the different Airbnb hosts. Constantiou et al. (2017) posit that hosts usually adopt the pricing recommendations set by Airbnb. In the perspective of my empirical section, this could be an interesting phenomenon to examine should the pricing of Airbnb accommodation prove either overly expensive, or very cheap and overly aggressive in pricing.

Table 3: Clustering of sharing economy business models by control and rivalry into four clusters. Constantiou et al. (2017)

CONTROL: **RIVALRY:**	**Tight** Platform participation is specified, standardized and monitored by the platform owner	**Loose** Minimum standards or guiding principles for platform participation are set by the platform owner
High Pricing schemes based on real-time changes in supply and demand	**The Franchiser** Prototypical example: ***Uber*** • Value proposition: Low costs and efficiency gains • Other examples: *Lyft, Postmates, Caviar*	**The Chaperone** Prototypical example: ***Airbnb*** • Value proposition: Service differentiation • Other examples: *Homeaway, Rentomo, Apprentus*
Low Pricing schemes based on compensation of the suppliers' costs	**The Principal** Prototypical example: ***Handy*** • Value proposition: Low costs and risk mitigation • Other examples: *TaskRabbit, Zeel, Deliveroo*	**The Gardener** Prototypical example: ***Couchsurfing*** • Value proposition: Self-organization and community building • Other examples: *BeWelcome, Blablacar, Peerby*

2.3 Pricing decisions & revenue management

2.3.1 Definitions

Revenue management as a concept aims to sell the right product to the right customer at the right time (Yeoman & McMahon-Beattie, 2017). In the 1950s, 1960s and 1970s the focus was on cancellations, no-shows and misconnections (Yeoman & McMahon-Beattie, 2017) and after the 70s this view was expanded to include data on advance bookings even 13 weeks before the event / flight / stay (Littlewood, 2005). The 'Littlewood' rule was expanded to become the foundation for airline revenue management systems (Belobaba, 1987).

At the core of revenue management is inventory control and yield management; and revenue management is interchangeably called yield management (Boyd & Bilegan, 2003). Inventory control aims to manage overbookings, avoid underbooking and in the perspective of yield management gain the highest profit of the seats in total. This means pricing airline seats or hotel rooms differently based on booking time and room / seat quality (Boyd & Bilegan, 2003; Yeoman & McMahon-Beattie, 2017).

2.3.2 Yield management & dynamic pricing

Challenges in performing yield management have much to do with dealing with demand uncertainty and perishability of products or capacity (Boyd & Bilegan, 2003; Perakis & Sood, 2006; Broderick, 2015). Retailers have proprietary algorithms crunching vast amounts of data and churning our prices that the consumer would be willing to buy (Broderick, 2015). Broderick states that dynamic pricing is constantly making its way to new industries. Software changes to prices according to parameters and even according to consumer websites to adjust prices in a matter of hours or even in a matter of minutes.

Revenue management systems that herald from the central reservation systems that logged in the sales of inventory at fixed price provide insight into customer purchasing habits and patterns. Baker & Collier (1999) examined data availability, data accuracy, forecast ability, computer capability and user understanding as criteria for understanding the process of forecasting demand. Contemporary systems employing even methods of machine learning have progressed in many of those factors since their research.

Much focus is placed on pricing on different fare classes (Boyd & Bilegan, 2003; Broderick, 2015). Similar considerations take place in hotels where hotel rooms charge different rates i.e. standard and deluxe rooms (Boyd & Bilegan, 2003). Challenge is caused by the existing dependency of demand between fare classes (Boyd & Bilegan, 2003). As detailed by Boyd & Bilegan (2003) about the misunderstood nature of yield management and dynamic pricing, should a fare class sell out day X then perhaps only more expensive classes are left for sale on day X+1. To customers this may appear as if dynamic pricing would have set the price higher, when in fact the price class is no longer available.

Examining revenue management is different based on the industry. While the airline industry is focused on maximizing profits per flight leg, hotels look to maximize profit from guests staying varying periods of time. Boyd & Bilegan (2003) discuss the challenge as hotels may receive many short duration bookings that block long duration stays and leave gaps in between guests.

2.3.3 Consumer dependent pricing

Krämer et al. (2017) discussed in their research the customer driven pricing mechanisms that they dubbed as Pay What You Want (PWYW) and Name Your Own Price (NYOP). They posit that the mentioned pricing strategies have been used in the past to good effect to achieve successful market entry. However, they note that both PWYW and NYOP have shortcomings especially when competing against in each other. In the context of hospitality industry the above pricing strategies can be employed to sell excess capacity when fixed costs are high (Krämer et al., 2017). Achieving some sales, which cover the variable costs can help off-set losses when capacity is not fully utilized with perishable products and services.

PWYW makes it possible for a customer to pay zero, which in turn allows for monopolizing the market. In contrast, NYOP uses thresholds for acceptable prices that the buyer suggests and the seller can choose to accept when the price is within their acceptable range. This pricing strategy allows sufficient market penetration, but yields higher profits (or limits losses.) Krämer et al. (2017) note that the pricing strategies mentioned in the previous chapter can be used to promote a company's offering to a wider audience. However, some friction between seller and buyer exists, when the seller is employing a PWYW pricing strategy. Buyers can be unwilling to purchase from a PWYW seller due to the discomfort associated with the price setting i.e. how much is a fair price instead of me being greedy type of scenario. The authors posit that direct promotional benefits alone are not sufficient to making a PWYW pricing model profitable.

There are some geographical differences to the feasibility of the two pricing strategies. A chief executive of Priceline (company known for its use of NYOP) has stated in the Wall Street Journal that a NYOP pricing model does not work as well in Asia and

Europe compared to the United States (Morrison, 2010). The executive cites uncertain levels of quality and consistency as contributing factors to the difference between the markets.

While the previous pricing methods are dependent on consumers determining the price, another consideration is the transparency that consumers receive of the prices they pay – or set. Yeoman & McMahon-Beattie (2017) posit that as the dynamics of pricing are more and more visible to consumers through price comparison websites and highly responsive websites and smartphone applications, customers are able to seek the best price available. They also note that nearly every hotel has a revenue manager (Yeoman & McMahon-Beattie, 2017), and Airbnb has a pricing algorithm that aids hosts in setting their prices (Steinmetz, 2015; Hill, 2015). There are, however, indications that Airbnb hosts are not satisfied with the transparency of the price recommendations that the platform provides, nor the level the platform suggest they charge their guests. Gibbs et al. (2017) highlighted the need for further education about pricing as needed from Airbnb. Example of frustrated users in the Appendix section is included in the appendix section (Picture C1). Furthermore, article by Hill (2015) indicates that their pricing tool provides a recommendation every day, yet it seems to require manual interaction from the host to accept the new suggested price. Dynamic pricing could be expected to perform this automatically instead of expecting hosts to check-in frequently to accept price suggestions. This could indicate that transparency in prices is not important only to the buyer but also the seller side.

Article by Steinmetz (2015) examined the released Airbnb pricing tool and mentioned an uncited Airbnb report that hosts that manually set their price within 5% of the Airbnb recommendation increased their likelihood of getting a booking by four times over. However, as mentioned by Steinmetz, the sweet spot can change quickly and furthermore if the bookings increased by four times over, does not necessarily mean the price is maximizing profits instead of occupancy rate. Neither of the articles provide insight into the customer-specific targets of occupancy, which may be lower and offset with a higher charged price for stay.

2.3.4 Predatory pricing

Predatory pricing is a highly debated subject in business practices and in competition policy (Niels & ten Kate, 2000). Recent occurrences (and perhaps the only one) in predatory pricing in Finland include the case against Valio’s pricing of milk (Yle.fi, 2016; Talouselämä, 2016; Maaseudun Tulevaisuus, 2017). In the court case the Finnish dairy company was charged with a fine of €70 million for predatory pricing, by setting the price of milk below variable costs. Valio held the view that costs to account for in the pricing should be held at market value instead of the view held by Finnish competition authorities that basic milk should account for 70% of the purchasing expenses of raw milk. (Talouselämä, 2016). Media relayed the image of a company, which forces competition out of the market. Niels & ten Kate (2000) state that competition has a tendency to complain to authorities for undercutting their prices and that steps have been taken in the past, which protect new entrants over economic efficiency.

Common criterion for definition among academic literature on predatory pricing is that it requires some form of below-cost pricing – and sometimes cases even above costs (Niels & ten Kate, 2000). The authors discuss the way in which companies can charge lower rates in one market, while charging higher rates in another (also called cross-subsidization). Current market players in taxi and hospitality industries have blamed disruptive sharing economy companies of undercutting their prices through circumventing regulatory demands. Hypothetically, it can be difficult to charge a sharing economy business of predatory pricing. Should the company give their users full authority to set the price they wish, would the company be expected to pay the penalties for a possible breach in fair competition?

Niels & ten Kate (2000) posit that a company's willingness to engage in predatory pricing constitutes an entry barrier and also an exit barrier for current market players. Prices would shift to a higher level after a possible entry is deterred and those remaining in the market can return to a higher price level. Considering the views presented in the previous two chapters, curious future research could be conducted on how cheap computing power can affect competition and prices. Should a sharing economy company exist in market across the globe, the company can enjoy scale benefits that market entrants can find extremely difficult to overcome. Companies such as Google and Facebook have caught the eyes of people looking to break up the companies as natural monopolies (New York Times, 2017a). Should sharing economy businesses rise to matchings heights in their successes, and a world order with reduced individual ownership take hold, how should these businesses be regulated?

2.4 Factors affecting prices in hotel industry

Several studies have been conducted in the past decades into hotel pricing determinants (Wang & Nicolau, 2017). Wang & Nicolau (2017) have categorized hotel price determinants into five categories listed in table 4. These categories are 1) site-specific characteristics, 2) quality-signaling factors, 3) hotel services, 4) property characteristics and 5) external factors. Some of these determinants have a positive effect on price, and others can have a negative impact based on conditions. Their research confirms many of the commonly accepted truths such a link between higher prices and proximity to a focal point in a city such as transport hub or tourism hotspot. However, the determinants mentioned work to make the hotel the chosen location for a traveler, other factors affect the total number of travelers to a location in general. Thus, normal rules of supply and demand apply and the more travelers you have travelling to a location, the higher the pressure of raising prices. This pattern can be observed in the graph below of hotel prices in London during (2015-2017). Additional figures can be found under the appendix section.

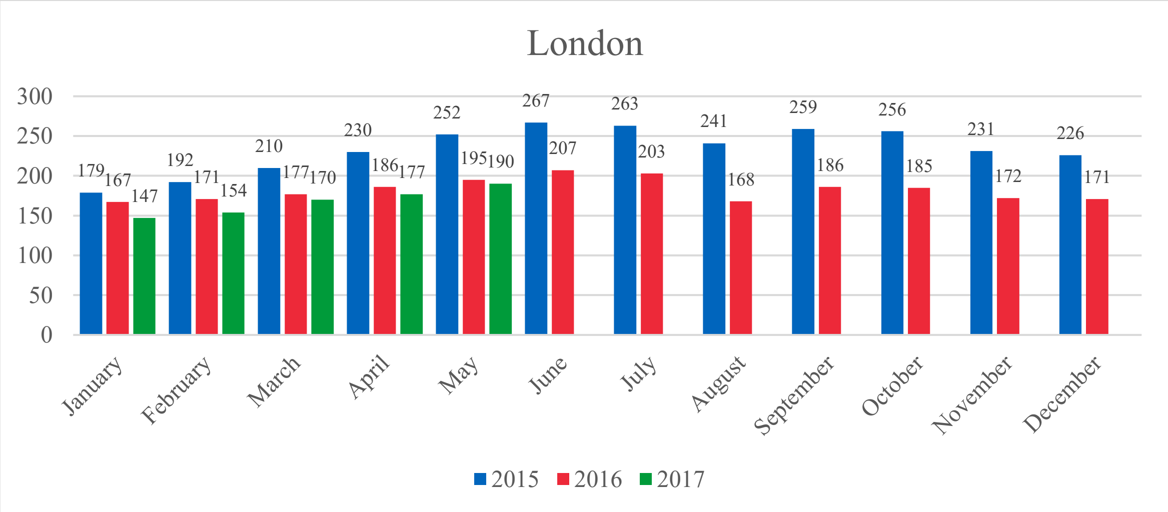

Figure 1. Price variation between high & low demand months in London. Source: Trivago

Wang & Nicolau (2017) noted that past research identified regional differences between the price determinants as to what the effect of offering a specific amenity, or the existence of parking or Wi-Fi has on the hotel pricing. The offering of amenities are mostly associated with an increase in pricing. Laundry services, however, affect prices negatively and provision of Wi-Fi has a mixed effect on prices. The researchers posited that newer hotels (budget hotels) carry lower prices and provide free internet, while older more traditional hotels charge extra for using Wi-Fi.

Table 4: Summary of hotel price determinants

Studies on hotel price determinants.

Dimension	Determinants	Effects	Literature	Details of previous studies
Site-specific Characteristics	Location (Distance to city center/transportation hub/major attractions/beach)	Significant & Negative	Bull (1994), Chen and Rothschild (2010), Hung et al. (2010), Lee and Jang (2012), Schamel (2012), White and Mulligan (2002), Zhang et al. (2011).	1. Bull (1994): 15 motels in Ballina, NSW, Australia; Hedonic pricing modeling. 2. Israeli (2002): 215 Israeli hotels; linear regression. 3. White and Mulligan (2002): 600 hotels in southwestern U.S. states; Hedonic price modeling. 4. Espinet et al. (2003): 82000 listed price from 1991 to 1998, Costa Brava, Spain; Hedonic price. 5. Thrane (2007): 74 hotels in Norway; OLS 6. Chen and Rothschild (2010): 73 hotels in Taiwan, Hedonic pricing method. 7. Hung et al., 2010: 58 Taiwan hotels; quantile regression. 8. Zhang et al. (2011): 228 hotels above three star in Beijing; hedonic price. 9. Schamel (2012): Online *meta*-booking engine trivago.com for hotels in 10 km vicinity of Bolzano; Hedonic model. 10. Lee and Jang (2012): hotels in Chicago, Spatial and Aspatial models. 11. Becerra et al. (2013): 1490 hotels in Spain; OLS. 12. Saló et al. (2014): 1092 hotels Costa Brava, Spain; OLS. 13. Masiero et al. (2015): Transaction data for accommodations in Ascona-Locarno, Ticino, Switzerland,; OLS and quantile regression. 14. Yang et al. (2016): hotels in caribbean, a three-level mixed effect linear regression model.
Quality signaling factors	Stars	Significant & Positive	Bull (1994), Becerra et al. (2013), Chen and Rothschild (2010), Israeli (2002), Masiero et al. (2015), Saló et al. (2014), Schamel (2012), Yang et al. (2016), Zhang et al. (2011).	
	Customer ratings	Significant & Positive	Schamel (2012) and Yang et al. (2016).	
	Chain affiliation or not	Mixed	**Positive:** Becerra et al. (2013), Chen and Rothschild (2010), Lee and Jang 2012), Thrane (2007), White and Mulligan (2002) and Yang et al. (2016). **Negative:** Hung et al. (2010) and Israeli (2002).	
Hotel amenities and services	Amenities (mini bar, TV, hotel safe, hair dryer)	Significant & Positive	Lee and Jang (2012), Schamel (2012), Thrane (2007).	
	Laundry service	Significant & Negative	Lee and Jang (2012).	
	Services (Express checkout, breakfast service, high ratio of housekeeper and guests, and advanced booking)	Significant & Positive	Masiero et al. (2015), Schamel (2012) and Yang et al. (2016)	
	Internet access	Mixed	**Positive:** Chen and Rothschild (2010), **Negative:** Schamel (2012) and Yang et al. (2016).	
Property characteristics	Car parking	Significant & Positive	Espinet et al. (2003), Lee and Jang (2012), Saló et al. (2014) and Thrane (2007).	
	Fitness center	Significant & Positive	Chen and Rothschild (2010) and Yang et al. (2016)	
External factors	The number and proximity of competitors	Mixed	Balaguer and Pernias (2013) and Becerra et al. (2013)	
	Low market accessibility	Significant & Positive	Yang et al. (2016)	

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2.5 Factors affecting prices in Airbnb accommodation

The effects of Airbnb listings on demand for hotel rooms is not fully understood, yet it has been identified that Airbnb does affect lower-end hotel accommodation more than high-end establishments Zervas et al. (2014). Research by Wang & Nicolau (2017) detailed the determinants that affect the prices of traditional hotels and examined the differences compared to Airbnb accommodation. For example the quality-signaling factors are different between the two, as Airbnb hosts act as individual entrepreneurs and are not chain affiliated nor are they awarded stars but are instead reviewed by the users. However, an integral link is identified through customer ratings, which played a significant role in not only price determination but also future bookings. Wang & Nicolau (2017) state that cheaper listings receive more bookings and consequently receive more ratings, which contributes to an identified negative effect of their variable "reviews per year".

Wang & Nicolau (2017) provide a detailed listing of determinants that either affect positively or negatively the Airbnb accommodation prices. These determinants have differences based on geographical location. For example, whether the host is a superhost or not has more importance in France than elsewhere. Similarly, the offering of breakfast with accommodation in Austria and France is not linked with a negative effect on price. This is contradictory to the status quo elsewhere in the world. Interestingly breakfast has the opposite effect on hotel prices.

Table 5: Determinants on Airbnb and hotel prices according to Wang & Nicolau (2017).

Determinant	Effect on Airbnb prices	Effect on hotel prices
Breakfast	Negative	Positive
Internet access	Positive	Mixed (newer cheaper hotels provide internet, traditional hotels may charge extra)
Distance to focal point	Negative (when further away)	Negative (when further away)
Customer ratings	Positive	Positive
Free parking	Positive	Positive
Stars	N/A or not in the study	Positive

Chain affiliation	N/A or not in the study	Mixed (some regions demonstrate a negative effect, mostly positive)
Superhost	Positive	N/A or not in the study
Host profile picture	Negative	N/A or not in the study
Verified host identity	Positive	N/A or not in the study
Entire home/apartment	Positive	N/A or not in the study
Private room	Slightly positive	N/A or not in the study
Number of people accommodated	Positive	N/A or not in the study
Bathroom	Positive	N/A or not in the study
Real bed	Positive	N/A or not in the study
Instant booking	Negative	N/A or not in the study
Flexible cancellation	Negative	N/A or not in the study
Smoking	Negative	N/A or not in the study
Reviews per year	Negative	N/A or not in the study

As can be gathered from the above table detailing the findings of Wang & Nicolau (2017), most determinants have the same effect on prices (both Airbnb and hotel). Some determinants are incompatible or not identified separately in their research, yet they identified two inconsistencies between the two forms of accommodation. As mentioned earlier, breakfast has a negative effect on Airbnb prices, although listings that provide breakfast only represent 9% of the listings in their sample. Considering user groups of sharing in section 2.2 (by Hellwig et al., 2015) and the theory by Wang & Nicolau (2017) that these hosts are looking to please their guests more, this could be an indication of a group not primarily interested in their economic benefit. This consideration is further enhanced by the link identified by Wang & Nicolau (2017) that flexible cancellation and low price are strongly related (27% of the sample).

Wang & Nicolau (2017) identify a negative link between the number of reviews and Airbnb price. They consider this to be caused by lower price accommodation having the most guests, which contributes a higher number of reviews than pricier locations. This is similar in the top 10% of the listings, where the cheapest among them receive most reviews. An interesting pattern to research further could be to identify whether having none or very few reviews contributes negatively in the booking rate of a location. This could force new hosts to lower the prices to reach the first bookings.

2.6 Impact of Airbnb on the hotel industry

Airbnb operates in the same markets as the hotel industry, but the effect on the industry itself is not fully understood (Zervas et al., 2014). While the previously mentioned authors only focus on Texas in their study, their findings provide an interesting view regardless of the limited representability of the wider phenomenon. Their research indicates that hotels that do not cater to business travelers are most affected by Airbnb listings. Therefore, the impact is not distributed evenly across the industry.

Zervas et al. (2014) indicate in their research that Airbnb listings in Texas is associated with lower returns for hotels. Their research reaches this conclusion by examining tax data from the state from the previous ten years and include Airbnb listing data from a previous five-year period.

Airbnb listings factor in an increase in supply on the market (Zervas et al., 2014). This in contrast to the demand side determinants examined in chapters 2.4 and 2.5 in this thesis. Furthermore, as Airbnb is in a growing phase and similar businesses are picking up speed, the effects are realized gradually (Zervas et al., 2014). They also consider in their research that many users have acted opportunistically when it comes to listing their property on Airbnb. People would therefore be taking advantage of low overhead costs of listing it an online platform (costs practically zero) and do not take care in weighing hotel performance in the area.

Yeoman & McMahon-Beattie (2017) discussed in their research the effect low-cost carriers (LCCs) had on legacy carriers. Legacy carriers faced severe cost cutting efforts to maintain financial viability, which eroded consumer perception of legacy carriers offering a better product. Boyd & Bilegan (2003) detailed the differentiation methods for hotels through free breakfasts, bathrobes and other amenities and Wang & Nicolau (2017) noted the positive effect of chain-affiliation on prices. Should Airbnb force hotels reduce their service level and included amenities, there exists a risk similar to the legacy carriers that perception of higher quality is eroded. A hotel aims to be a temporary “home” on your business journey or holiday, an Airbnb house / apartment often already is someone else’s home and may provide more of a feeling of being at home than a hotel in the future. Further research on this topic would be needed, however, to examine this possibility more closely.

2.7 Summary of literature review

Topic	Findings	References
Differences in terminology of sharing economy	▪ Sharing itself is as old as humankind ▪ Sharing economy gained identification in the 2000s ▪ Different terms (collaborative consumption, sharing economy, commercial sharing systems) are used interchangeably ▪ Sharing economy looks to take advantage of underutilized assets by making them online; either in open (public) or closed (restricted) sharing ▪ Peer-to-peer sharing may become a new way for traditional companies to do business	Belk (2014), Richardson (2015), Lamberton & Rose (2012), Huefner (2015)
Criticism of sharing economy	▪ Sharing economy is more similar to short-term rentals and lending rather than true sharing ▪ Traditional companies face an unlevel playing field, results in fight-or-flee situations ▪ Sharing an alternative to hyperconsumerism or neoliberalism on steroids? ▪ Sharing increases the use of an asset which may have negative environmental impact depending on the asset i.e. the rebound effect	Belk (2014), Richardson (2015), Cusumano (2015), Botsman & Rogers (2010), Morozov (2013), Scheepens et al., (2016)
Sharing economy business models with *a user dependent view*	▪ Business model is heavily dependent on consumer needs in the target market ▪ Hellwig's clustering of users (normatives, opponents, pragmatists & idealists) based on characteristics and motivations ▪ A consumer's materialism (desire to own things) is a hindrance to sharing participation ▪ Managers can affect the perceived risk of shared resource scarcity by designing the system can communication carefully	Lamberton & Rose (2012), Hellwig et al. (2015), Akbar et al. (2016), Behrendt et al., (2013)
Sharing economy business models with *a resource dependent view*	▪ Offering unique products can also capture also materialistic consumers in the business model ▪ Extended self limits sharing willingness ▪ Sustainability comes from saving energy in the use phase over old product, rebound affect still applies, however ▪ Sharing willingness in Hellwig's user clustering is dependent on resource category and cluster	Akbar et al. (2016), Hellwig et al. (2015), Belk (1988), Scheepens et al. (2016), Vogtländer et al. (2014), Constantiou et al. (2017)

	▪ Sharing economy business models can be categorized by examining the level of rivalry and control they face	
Pricing and revenue management	▪ Revenue management and dynamic pricing often mistakenly used interchangeably ▪ Revenue management deals with pricing capacity in different classes, while dynamic pricing adjusts the prices overall ▪ Revenue management looks to sell the right product to the right customer at the right time ▪ Since the 50s, 60s and 70s, revenue management has dealt with cancellations, no-shows and misconnections and has since expanded to include data on advance bookings ▪ Challenge in yield management is dealing with demand uncertainty and product or capacity perishability	Boyd & Bilegan (2003), Yeoman & McMahon-Beattie, (2017), Boyd & Bilegan, (2003), Perakis & Sood, (2006), Broderick, (2015)
Consumer dependent pricing	▪ Consumers determine the prices they want to pay in Pay What You Want (PWYW) and Name Your Own Price (NYOP) pricing models, PWYW enables extremely high market penetration, however, even promotional benefits cannot make it profitable in the long run ▪ Consumers pursue transparency in pricing, and modern systems offer greater access to information ▪ Airbnb users that set their price within 5% of the price recommendation increase booking likelihood by four times over	Krämer et al. (2017), Yeoman & McMahon-Beattie (2017), Hill (2015), Steinmetz (2015)
Predatory pricing	▪ Predatory pricing remains a highly debated subject in business practice and competition policy ▪ Companies have a tendency to complain to authorities for undercutting their prices ▪ Past steps which have been undertaken in markets have served to protect new entrants over economic efficiency ▪ Defined as below-cost pricing, cases of above costs have been prosecuted as well	Niels & ten Kate (2000), various media outlets
Hotel price determinants	▪ Determinants distributed into three categories: 1) site-specific characteristics, 2) quality-signaling factors, 3) hotel services, 4) property characteristics and 5) external factors ▪ Proximity to a focal point such as transport hub or tourism hotspot have a positive effect on prices ▪ Regional differences persist and certain amenities have a mixed effect on price	Wang & Nicolau (2017)

Airbnb price determinants	▪ Airbnb price determinants are not fully similar to hotel price determinants (some are not applicable and others have divergent effect on price) ▪ User groups may influence Airbnb offering and consecutively on pricing ▪ Users with lower prices get the most bookings and more reviews	Zervas et al. (2014), Wang & Nicolau (2017), Hellwig et al. (2015)
Impact of Airbnb on hotel industry	▪ Airbnb's effect on the hotel industry is not fully understood, however Airbnb listings (in Texas) affects the lower-end hotels' profits the most ▪ Airbnb listings constitute a supply side shock, which increases competition ▪ Airbnb and similar businesses are still at growth stage and effects are realizing gradually ▪ People have behaved opportunistically and may not fully understand their own cost structures and those of their hotel competitors ▪ Low-cost carriers had a strong effect on the viability of legacy carriers and on the consumer trust of them offering a superior product ▪ Hotel differentiation may change due to Airbnb's influence, would this have a similar effect as with airlines	Zervas et al. (2014), Yeoman & McMahon-Beattie (2017), Boyd & Bilegan (2003), Wang & Nicolau (2017)

3 Methodology

3.1 Chosen approach

This thesis will approach the research problem with a quantitative data analysis based on available data on Airbnb listings, bookings and price data through Insideairbnb.com and will be aggregated using SQL to provide data sets for analysis and graphs for visualizing key findings (processing of data detailed in Figure 2). Twelve cities across the globe have been selected for the comparison, which represent major cities in Northern America, Western Europe and Australia. Hotel data for the comparisons are from Trivago hotel price indices, which detail monthly averages for two person hotel rooms.

Meredith (1998) has defined that case studies can employ multiple methods and tools for data collection to consider both temporal and contextual elements of the studied phenomenon. Yin (2009) has described a case study as a way to review new or unclear phenomena while maintaining a holistic real-life view. Meredith (1998) and Yin (2009) have identified financial data and other organizational charts as potential sources for intelligence – among others. This research is limited into the hospitality industry as comparing data between industries is beyond the chosen research scope. This research will look to explain potential differences in price setting between traditional firms and sharing economy business models and will thus be a comparative case study. Airbnb is selected to be the focus due to its leading status in the industry and will be compared to an aggregated view of hotels through a price index.

Meredith (1998) has identified that case studies can employ both quantitative and qualitative approaches. Empirical data for the research is derived from Airbnb listing calendar data, which is aggregated to allow for identifying host tendency to set different prices at different times. This data is then compared to hotel price index data by matching the two data sources to examine the price deviations. The benefit of using the above approach is the large data sample with which to analyze Airbnb pricing, and the aggregated results provided by one of the largest online hotel booking websites (Trivago).

Eisenhardt (1989) and Glaser & Strauss (1967) discuss the divergent purposes of sampling and statistical sampling. According to them statistical sampling aims at obtaining accurate statistical evidence on distributions of variables within the population. Meredith (1998) discusses the way of increasing the generalizability of the study through testing the theory on alternative populations. My research will focus on populations across several countries and continents even, which will provide a large geographical scope to understand the phenomenon more widely. However, this research will focus only on one industry.

Ability of individual citizens (or hosts) to do pricing decisions in sharing economy is determined by examining price variation in several cities across the globe in the past 18-24 months. Comparisons will be made between price variations by month in Airbnb and hotel accommodation. Changes in the average prices between months provides insight on citizens' willingness and preparedness to adjust based on demand. This type of comparison highlights the extent of information and time that hosts have for setting their prices.

The described method has some limitations that need to be taken into consideration in the data preparation phase, data analysis phase and when deriving conclusions. One key limitation is the nature of data available on insideairbnb.com. Instead of having a data set with all prices at which locations were rented, the data available provides detailed booking information for the next 12 months each Airbnb listing in each report. Some of these calendar dates are shown as 'free' noted by an 'f' or booked 't' (detailed further in Table 7). However, both the host and guest may cancel the reservation before the stay. These listing reports are available from each location as follows.

Table 6: Data points and data point dates per city

City	# of data points, first and last data point dates
Amsterdam	7 data points between April 2015 and April 2017
Barcelona	7 data points between April 2015 and April 2017
Berlin	19 data points between October 2015 and May 2017
London	6 data points between April 2015 and March 2017
Los Angeles	11 data points between May 2015 and May 2017
Melbourne	8 data points between July 2015 and April 2017
New Orleans	10 data points between June 2015 and June 2017
New York City	27 data points between January 2015 and May 2017
Paris	4 data points between May 2015 and April 2017
San Francisco	7 data points between May 2015 and April 2017

Sydney	8 data points between May 2015 and April 2017
Toronto	7 data points between June 2015 and June 2017

This creates gaps between the data in certain cities, which requires using booking data from several months before the actual stay. Future research with more significant financial backing could use the reports sold by commercial companies, which charge up to $80 per report for each city. However, with 121 data points detailing the listings in each location (totaling in tens of thousands) with the full availability calendar of 365 days I am provided an extensive sample (500+ million rows of price data).

Comparability between hotels and Airbnb accommodation has the caveat of very heterogeneous listings. Every hotel listing has different star ratings, some are in the city center while others are at the edge of the city. Airbnb listings are even more varied by being of all sizes that apartments can be. The accommodation can be a shared room, private room or an entire apartment or house. Therefore, a determination such as "hotel is cheaper than Airbnb" in a specific month in a city cannot be made definitively, nor is that the objective of this thesis. However, with locations in each city reaching tens of thousands and countless hotels in large cities, the effect of having a highly heterogeneous data mass is diluted.

Table 7: Columns in raw data sets of Airbnb pricing and calendar booking information

Airbnb raw booking data columns		
Listings data file		
id	=	ID of listed Airbnb accommodation (city-specific)
name		Name of the Airbnb listing (user-given)
host_id		ID of the listing's host
host_name		Name of the listing's host
neighbourhood_group		Region of the city
neighbourhood		Sub-region of the city
latitude		GPS coordinates
longitude		GPS coordinates
room_type		Type of accommodation (entire home/apt, private room, shared room)
price		Price of stay
minimum_nights		Minimum nights of reservation
number_of_reviews		Number of reviews the listing has received
last_review		Date of last review
reviews_per_month		Number of reviews per month
calculated_host_listings_count		Number of listings the host has available for rental
availability_365		Approximation of how many days the listing is available
Calendar data file		
Listing_ID	=	ID of listed Airbnb accommodation (city-specific)
Date		Calendar date for booking
Available		Identifier (f or t) for whether the listing has been booked/taken = t, or is free for booking =f
Price		Price of stay for booked night (value null if Available = f)

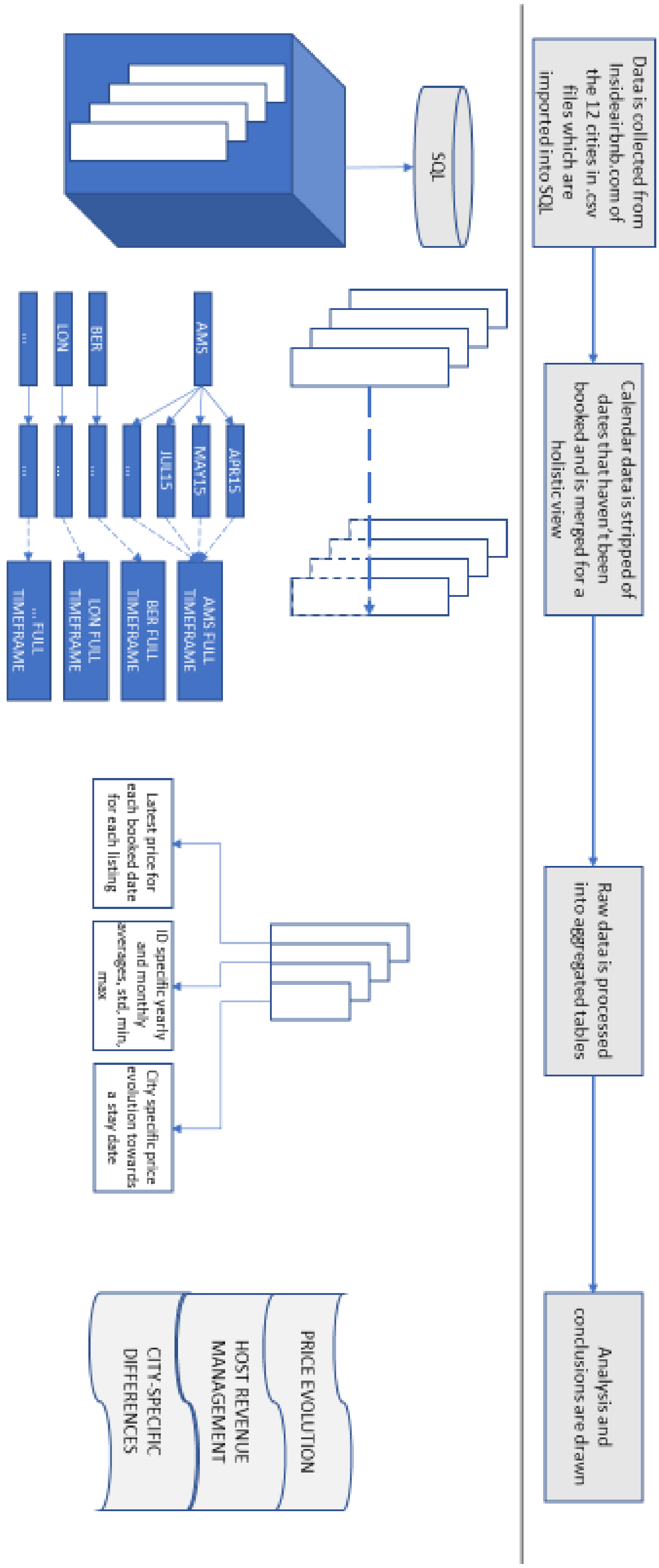


Figure 2. Description of steps taken to process raw data for analysis in section 4

3.2 Description of Airbnb's business model & market situation

Airbnb is a company founded in 2008 for acting as a marketplace to offer locations for short-term rental (Airbnb.com). Private citizens can list their property on the marketplace (today also professional lodging has appeared on the website), where other people can browse for a location to stay during their holiday, business trip, weekend away, etc.

Airbnb allows the hosts, who rent their apartment set the price they wish to charge their guests, and Airbnb takes a percentage of that price. The company has developed their pricing mechanism along the years, and it provides hosts a recommendation – or tip – on what the price for a specific date could be. Ultimately the decision to select the price is left with the host, however. Several new businesses have emerged around Airbnb to provide hosts with an extended set of tools and automation even to manage their listed property/properties more effectively and promise higher returns on their listings. What this would suggest, and I will discuss further in the literature review section is that Airbnb's pricing tool is incomplete and lacking in transparency – especially for more professional hosts.

Airbnb has faced considerable opposition from hotel chains, who feel that the startup turned international phenomenon is in violation of the law, avoids taxation and is in non-compliance of regulations placed on the hospitality industry across the world. As described by them this unleveled playing field between hotels and Airbnb results in a lower overhead and variable cost for Airbnb hosts, which enables them to undercut hotel prices.

4 Findings and discussion

In this section I will discuss the key findings based on the Airbnb rental booking and price data and provide visualizations of the data.

4.1 Data overview

4.1.1 Managing Airbnb price data

Data files available for download through Insideairbnb.com give access to files with differing content. In this analysis, the bulk of data is derived from the calendar data files. Calendar data files contain the columns Listing_ID (Airbnb rental location specific), calendar date, identifier signaling whether the listing is booked or free for the specific date and finally the price of the rental in local currency.

Calendar data is saved in individual .csv files, which are ported to be managed in SQL (each file has rows from a few million to tens of millions). Unnecessary rows (calendar dates of listings with no bookings and subsequently no price data) are deleted from the data and data from separate .csv files is merged into a single SQL table with the most current price information available. Additionally, another table is created where the monthly maximum, minimum, average and standard deviation values are calculated per month for each listing.

Another course of analysis is enabled by calculating average prices in each of the calendar.csv files. This enables analyzing whether the price is higher or lower closer to the actual stay.

Second data source contains an overview of listing in each city location. This data file is used in this research to describe the different categories of listings. The file's information is not merged in this research with the data of the first file due to time and resource constraints. Thus, an accepted variance is to be accepted within the research: Airbnb listings are not differentiated in the research whether they are shared rooms, private rooms or entire apartments. Private rooms and entire apartments represent the bulk of the listings as detailed in the graphs below. Respective percentages of each accommodation type have developed during the analysis period.

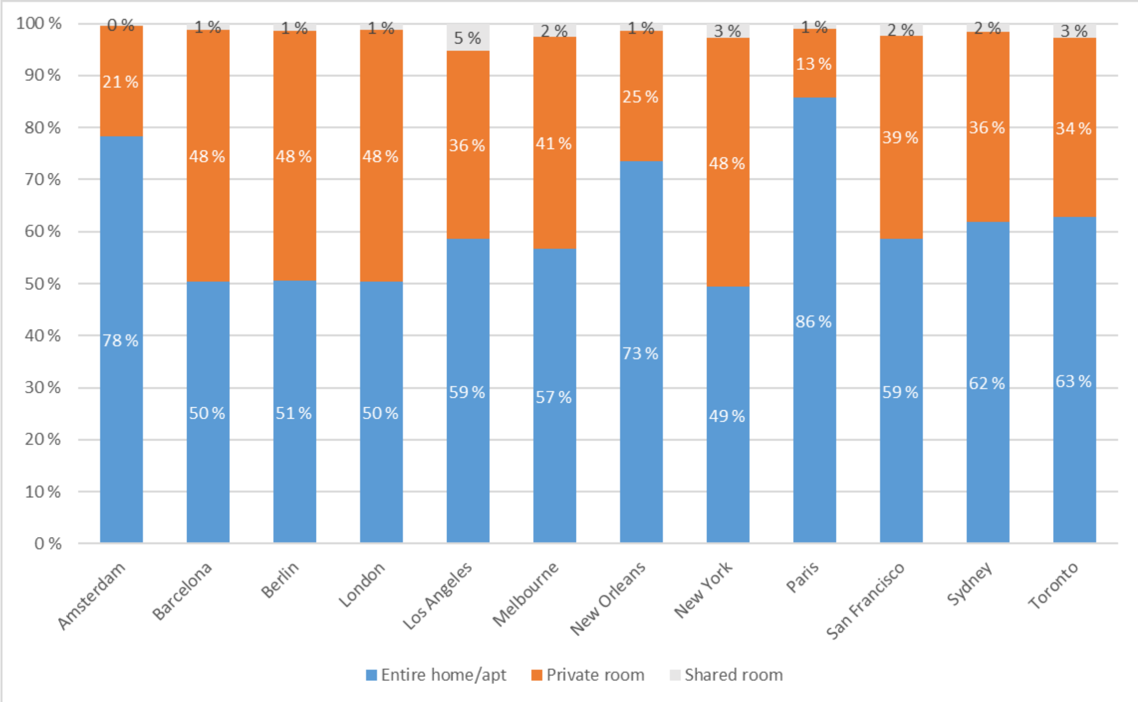


Figure 3. Distribution of accomodation type by city (status at end 2016 / early 2017)

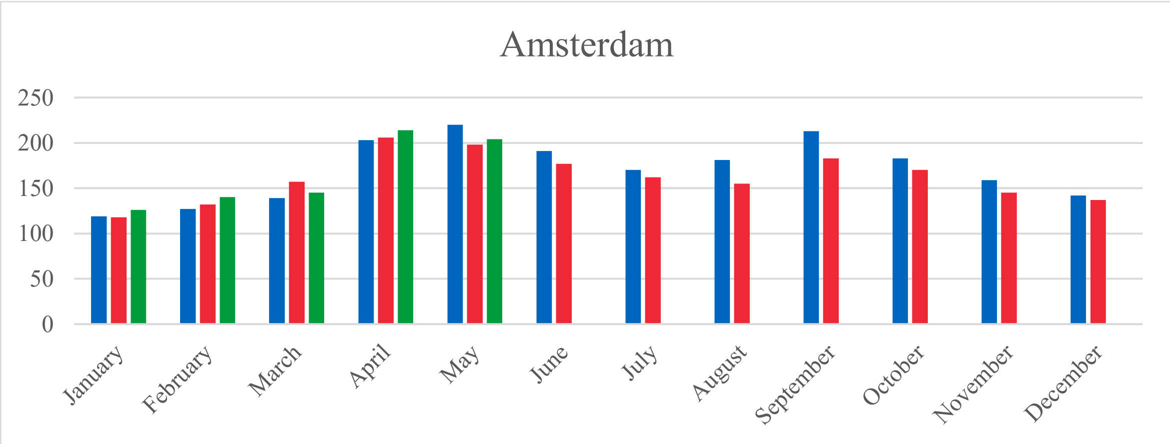
The listing file also enables ascertaining how Airbnb has developed in each of the cities in terms of growth rate. Other variables could be analyzed in subsequent research, but are not discussed in this thesis. More detailed tables and graphs of the cities are available under the appendix section.

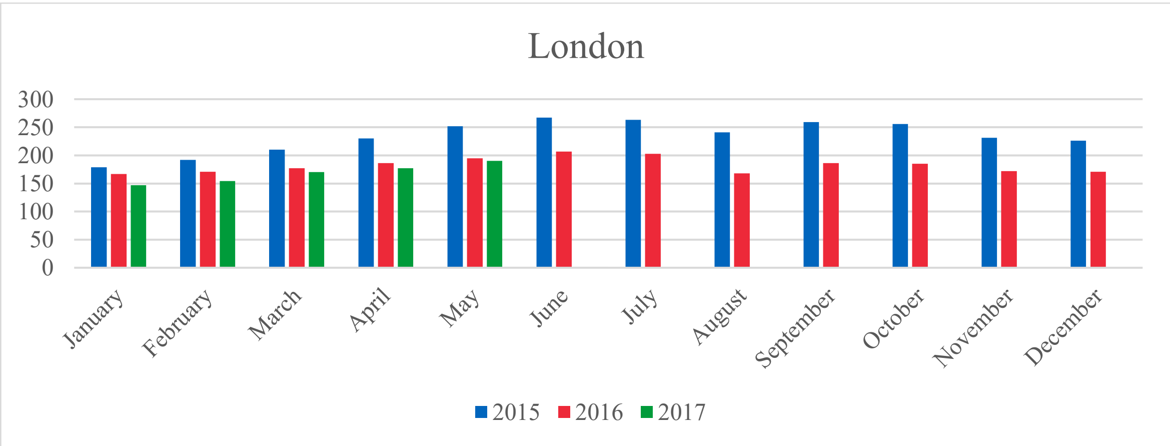
Table 8: Summary of change in accommodation type in each city (change in percentages)

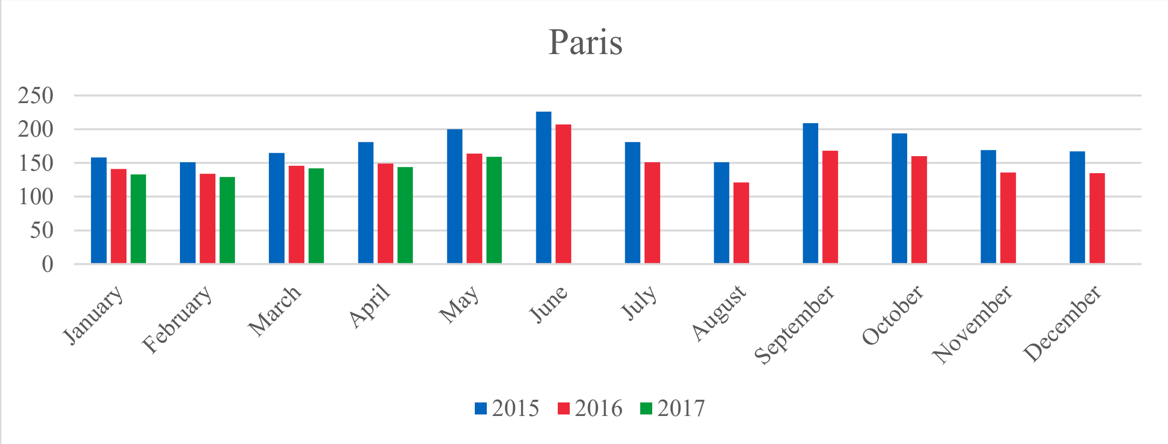
	Entire home/apt	Private room	Shared room	Growth
Amsterdam	-2 %	2 %	0 %	93 %
Barcelona	-9 %	8 %	1 %	44 %
Berlin	-10 %	10 %	0 %	25 %
London	-2 %	2 %	0 %	193 %
Los Angeles	-1 %	0 %	2 %	62 %
Melbourne	5 %	-5 %	0 %	126 %
New Orleans	6 %	-6 %	0 %	108 %
New York	-9 %	9 %	0 %	49 %
Paris	2 %	-2 %	0 %	95 %
San Francisco	-1 %	3 %	-2 %	61 %
Sydney	2 %	-3 %	0 %	145 %
Toronto	-1 %	1 %	0 %	109 %

4.1.2 Trivago hotel price indices

Airbnb data is compared to hotel price indices drafted by Trivago for years 2015-2017 by month. Trivago has calculated the average prices for hotel rooms in several locations across the globe. In the calculation they have counted the average price for a two-person room. Comparison of hotel and Airbnb rooms would be difficult due to different room sizes, countless locations. Thus, deriving findings about which is cheaper is not a possibility, however nor is it a point of interest in this research. What is, however, observable from the visualized statistics how hotel prices have evolved and greatly reduced in the timeframe 2015-2017 in locations such as Amsterdam, London and Paris. Further examination should be performed before making further statements, as these three locations have all experienced recent terrorist attacks, which may have affected passenger flows. Growth rates are not consistent across locations, however. Further tables are included in the Appendix section.







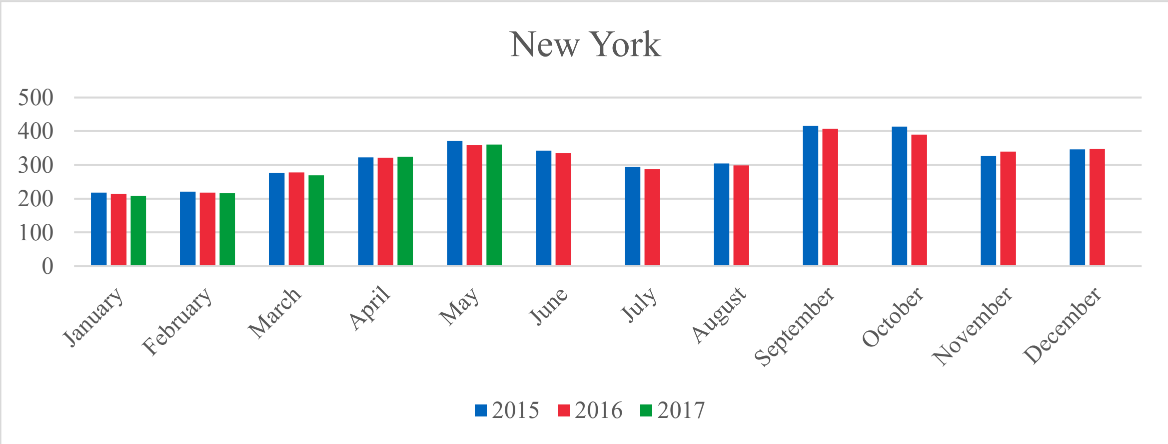


Figure 4. Hotel price indices detailing price variation across locations in 2015-2017. Source: Trivago

The data will be used to derive views that provide answers to the research questions. Graphs and views will be drafted to show whether Airbnb prices rise similarly to hotel prices (higher prices the closer the actual date is). Secondly, to show how much Airbnb prices adjust based on demand high- & low-points and thirdly to detail what the proportions of hosts that do active revenue management either by themselves or by using third-party tools. However, as this study is quantitative in nature and the data source does not provide a way of determining whether a host is using third-party software to boost their revenue management, distinctions cannot be made between the two. By engaging in revenue management hosts are able to enhance their profits. Hellwig et al. (2015) and Akbar et al. (2016) detailed in their research user clusters that they identified as sharing economy users. I will hypothesize about these segments from the findings arrived at through this research and draw links between their research.

4.2 Airbnb price evolution

Tables below detail how prices develop as the stay gets closer. The furthest data point is 12 months our and closest data point is 0 months out. Difference to end price details what is the difference in average prices to the closest price information available for a stay (end price). Price evolution details the direction the price has developed since the last month's average price.

Tables indicate that regional differences exist in terms of how prices develop, which has different implications. New York indicates a direction that is opposite to the general rule that comes to booking a hotel stay – booking early usually means saving money. Based on the data in 2016 and 2017, booking an Airbnb accommodation is best left until only a few months beforehand. Prices start at a high level (in 2016 price difference was over $10 from the final price 5-11 months before the stay). In 2017, the prices remained low or lower than the end price from 8-12 months before the stay and remaining higher than the final price 3-7 months before stay.

Table 9: Detailing price evolution in New York City during 2016-2017.

New York City	Difference to end price			Price evolution		
Months before stay	2016 & 2017	2016	2017	2016 & 2017	2016	2017
0				-0,93	-0,96	-0,88
1	-0,49	-1,25	0,88	-1,28	-2,75	1,16
2	0,81	1,55	-0,42	-5,37	-5,35	-5,39
3	6,72	7,90	5,03	-1,68	-2,61	-0,52
4	7,49	9,55	4,92	-0,36	-0,90	0,24
5	8,10	11,66	4,14	-1,66	-3,02	-0,29
6	8,87	14,26	4,02	0,52	-0,18	1,10
7	7,12	12,69	2,55	0,26	-0,76	1,03
8	6,39	13,17	1,31	-0,45	-1,83	0,59
9	7,23	15,91	0,73	-0,05	-1,23	0,83
10	7,05	16,50	-1,54	3,15	6,17	0,73
11	6,09	16,64	-2,55	6,03	20,10	0,75
12	-6,81	-7,33	-6,55			

Table 10: Detailing price evolution in Toronto during 2016-2017.

Toronto	Difference to end price			Price evolution		
Months before stay	2016 & 2017	2016	2017	2016 & 2017	2016	2017
0				6,43	2,61	8,98
1	-5,65		-5,65	0,08	2,54	-0,53
2	-11,58		-11,58	-2,40	-0,28	-2,93
3	-11,83		-11,83	-2,04		-2,04
4	-8,72		-8,72	-2,33	0,32	-2,99
5	-2,66	10,19	-6,94	-2,09	-0,14	-2,58
6	-2,55		-2,55	1,06	0,55	1,18
7	-0,14	-0,32	-0,09	-1,15	-0,14	-1,48
8	-2,02	0,14	-2,56	0,09	-1,62	0,95
9	-3,46	-0,55	-4,43	-1,46	-2,22	-0,69
10	-1,55	-7,64	4,55			
11	-2,81	-0,46	-5,15			
12	-3,60	1,25	-8,45			

4.3 Individuals' pricing behavior

The aggregated results from the twelve cities can be observed in the three tables below. (Note: totals for rows can exceed 100%) Standard deviation indicates the variation in prices in each of the Airbnb listings. Listings have bookings from January to December in each of the years excluding the latter half of 2017 (data included until May 2017) and from 2015 in some of the locations, which may contribute to the development detailed in the graph below. Data from Berlin and Melbourne do not include data of the dates in 2015, thus only ten cities' data influence the figures for that year.

These figures indicate that a majority of people across cities engage in minimal revenue management with their yearly price deviation either zero or under ten (on average ~70% of listings.) Interestingly, users that receive a lot of bookings demonstrate a higher price deviation on average than overall. What this could indicate is learning curve effects about pricing: hosts are able to price their listing more efficiently and able to reach a higher revenue with their listing. This assumption expects that hosts knowingly adjust their pricing higher to match demand spikes. This way they can receive higher profits during high-season and weekends. In contrast, they also would adjust prices lower to maintain booking level at times with low demand

Table 11: Aggregated figures on price deviation across the 12 cities

	2015 - Percentage of listings with price deviation of									
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
All bookings	42,03 %	28,75 %	14,15 %	7,83 %	5,07 %	4,09 %	3,31 %	3,00 %	2,82 %	3,94 %
Listings with >90 bookings	33,79 %	30,58 %	16,68 %	9,02 %	5,95 %	4,74 %	3,70 %	3,22 %	2,95 %	4,45 %
Listings with >180 bookings	30,51 %	30,89 %	16,89 %	9,48 %	6,53 %	5,74 %	4,34 %	3,81 %	3,59 %	6,33 %

	2016 - Percentage of listings with price deviation of									
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
All bookings	39,00 %	31,48 %	13,71 %	7,69 %	5,12 %	4,20 %	3,42 %	3,11 %	2,86 %	4,39 %
Listings with >90 bookings	29,92 %	35,77 %	16,09 %	8,76 %	5,67 %	4,47 %	3,66 %	3,24 %	2,92 %	4,58 %
Listings with >180 bookings	26,57 %	36,47 %	17,21 %	9,29 %	5,95 %	4,73 %	3,85 %	3,33 %	2,97 %	4,71 %

	2017 - Percentage of listings with price deviation of									
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
All bookings	34,83 %	35,08 %	13,73 %	7,58 %	5,22 %	4,31 %	3,53 %	3,17 %	2,92 %	4,63 %
Listings with >90 bookings	25,89 %	38,09 %	15,94 %	8,65 %	5,98 %	4,76 %	3,89 %	3,43 %	3,12 %	5,32 %
Listings with >180 bookings	25,31 %	37,11 %	16,04 %	8,87 %	6,24 %	4,97 %	4,06 %	3,59 %	3,19 %	5,69 %

The above tables detail the average spread of standard deviation based on the number of bookings in the twelve cities. Large differences exist between locations, however. The contrast between locations is perhaps most felt by comparing the two charts below detailing the spread of standard deviation in Paris and New Orleans during 2016. In Paris across all booking activity levels, 75% - 80% of hosts show a yearly price standard deviation of less than ten. In New Orleans 18% - 30% show a price standard deviation or under ten while around 50% fall in the range STD $\in$ [20, 50] and near 25% have a yearly price standard deviation of 50 or more.

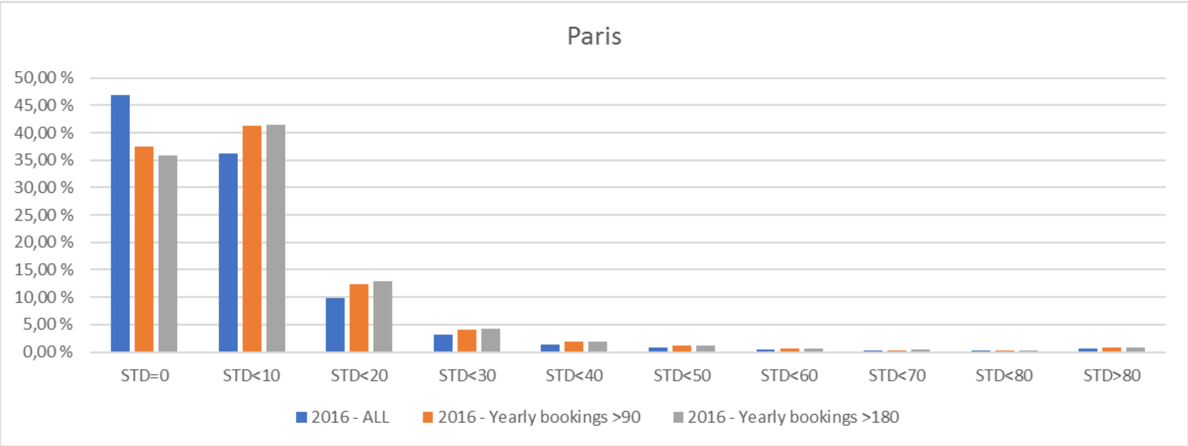


Figure 5. Chart detailing the spread of price standard deviation in Paris in 2016.

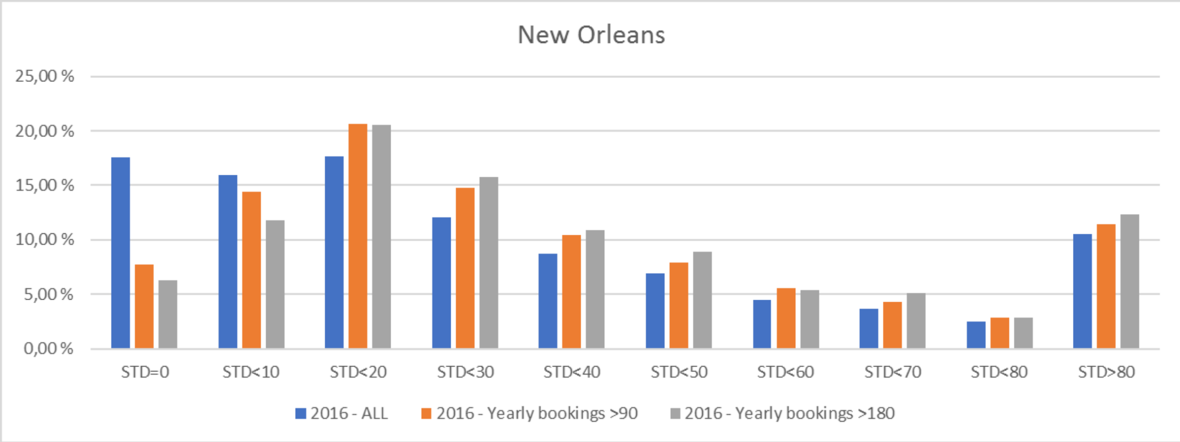


Figure 6. Chart detailing the spread of price standard deviation in New Orleans in 2016.

I previously discussed the possibility of learning curve effects with hosts that receive more bookings than overall. The chart below examines the development of average price standard deviations across the twelve locations. As discussed earlier, the years 2016 and 2017 contain data from twelve locations and 2015 contains the data of ten cities, which should not be disregarded when analyzing the results. A clear trend does, however, seem apparent by comparing these three years together. As each year passes hosts with more than 90 bookings seem increasingly conscious about performing revenue management. The same trend holds for those with over 180 bookings per year.

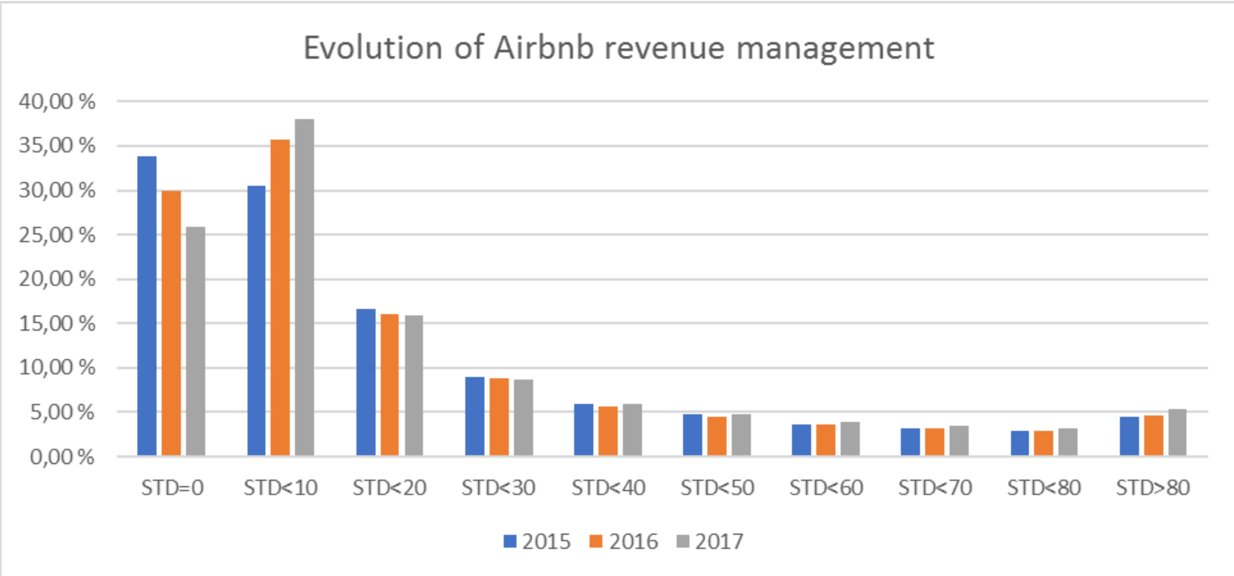


Figure 7. Detailing the evolution of revenue management in the twelve cities during 2015-2017.

In the table on the following page is a compilation of the twelve different locations. The table details the percentages of listings with under 90 bookings during 2016, over 90 bookings during 2016 and over 180 bookings during the year. Detailed in the table are also the average price standard deviation in that city during 2016 and the price standard deviation based on Trivago’s hotel price indices. By examining the percentage of users reaching these levels, we can ascertain how active hosts are in those locations, which combined with the information about bookings and price deviation detailed earlier, facilitate in deriving conclusions about the data.

Table 12: Summary of the twelve locations detailing host data characteristics

	2016 - Listing booking activity											
	Amsterdam	Barcelona	Berlin	London	Los Angeles	Melbourne	New Orleans	New York	Paris	San Francisco	Sydney	Toronto
< 90 bookings	58,7 %	48,8 %	72,5 %	57,7 %	49,2 %	52,9 %	50,3 %	73,5 %	43,7 %	52,5 %	56,7 %	53,8 %
> 90 bookings	29,3 %	27,1 %	22,7 %	28,1 %	34,6 %	28,8 %	29,9 %	19,7 %	30,9 %	33,2 %	24,0 %	29,4 %
>180 bookings	12,0 %	24,1 %	4,8 %	14,1 %	16,1 %	18,2 %	19,8 %	6,8 %	25,4 %	14,3 %	19,4 %	16,8 %
Average Price Std.	11,80	30,95	22,77	7,96	28,33	11,31	35,83	14,68	22,81	22,54	20,20	10,17
Comparative Hotel Price Std.	25,47	26,92	13,42	13,11	15,66	24,78	28,79	57,81	21,36	38,69	17,00	22,03
% of users reaching average price std.	30,89 %	10,83 %	4,79 %	25,71 %	11,25 %	28,12 %	31,18 %	27,85 %	5,81 %	23,40 %	20,96 %	24,70 %
% of users reaching hotel price std.	12,60 %	12,85 %	9,78 %	16,50 %	20,23 %	13,55 %	37,81 %	3,90 %	6,41 %	14,11 %	23,46 %	12,62 %

	Magnitude of revenue management, polarization of user mass											
	Amsterdam	Barcelona	Berlin	London	Los Angeles	Melbourne	New Orleans	New York	Paris	San Francisco	Sydney	Toronto
Average Price Std.	11,80	30,95	22,77	7,96	28,33	11,31	35,83	14,68	22,81	22,54	20,20	10,17
Rank of Airbnb rev. man.	9	2	5	12	3	10	1	8	4	6	7	11
Comparative Hotel Price Std.	25,47	26,92	13,42	13,11	15,66	24,78	28,79	57,81	21,36	38,69	17,00	22,03
Rank of hotel rev. man.	5	4	11	12	10	6	3	1	8	2	9	7
% of listings reaching average Airbnb price std.	30,89 %	10,83 %	4,79 %	25,71 %	11,25 %	28,12 %	31,18 %	27,85 %	5,81 %	23,40 %	20,96 %	24,70 %
Rank of polarization within host mass	11	3	1	8	4	10	12	9	2	6	5	7
% of listings reaching average hotel price std.	12,60 %	12,85 %	9,78 %	16,50 %	20,23 %	13,55 %	37,81 %	3,90 %	6,41 %	14,11 %	23,46 %	12,62 %

Notable in the data is the variance between the twelve cities with some locations prominent with occasional hosts with less than 90 bookings during the year such as New York (73,5%), Berlin (72,5%), Amsterdam (58,7%), London (57,75). Comparatively some locations show booking levels where hosts book their listing for 90 days or more per year: Paris (56,3%), Barcelona (51,2%), Los Angeles, New Orleans (49,7%). When considering the findings by Lee (2016) about inhabitants of Los Angeles no longer renting their apartment solely to pay for rent, instead making money while doing so, the cities mentioned first could be understood as emphasizing small earnings instead of the second group, which rents out a location more often solely for extra profit that is not necessary to pay for rent.

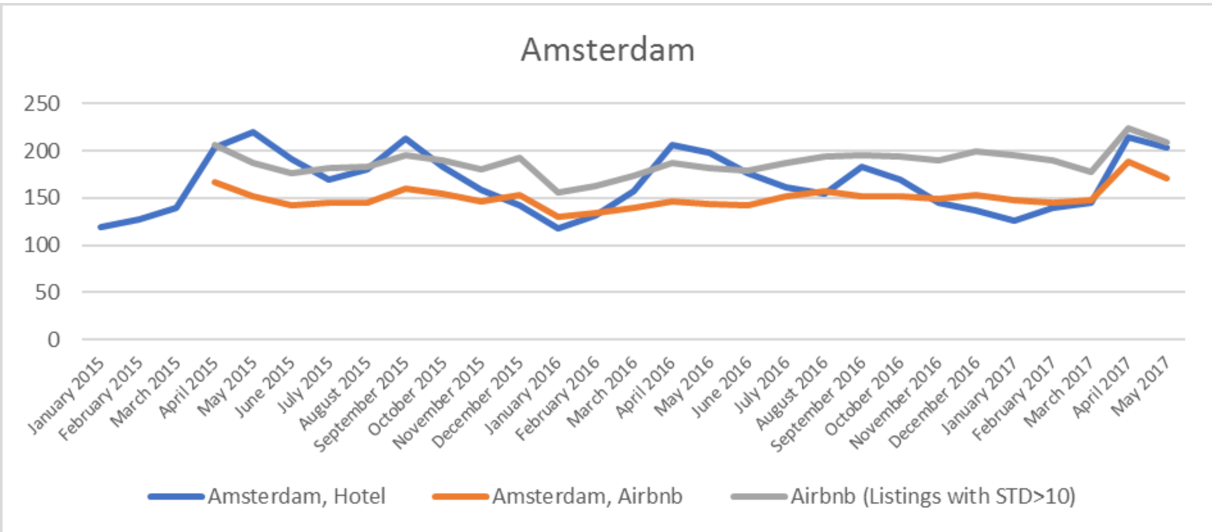
Interestingly, on average half of the cities indicate that Airbnbs have a higher standard deviation than hotels (Barcelona, Berlin, Los Angeles, New Orleans, Paris and Sydney.) Meanwhile locations such Amsterdam, London, Melbourne, New York, San Francisco and Toronto show higher price variation. In the cities where hotels' revenue management creates very strong seasonal differences compared to Airbnb the hotels adjust their prices on average 17 euros / dollars more.

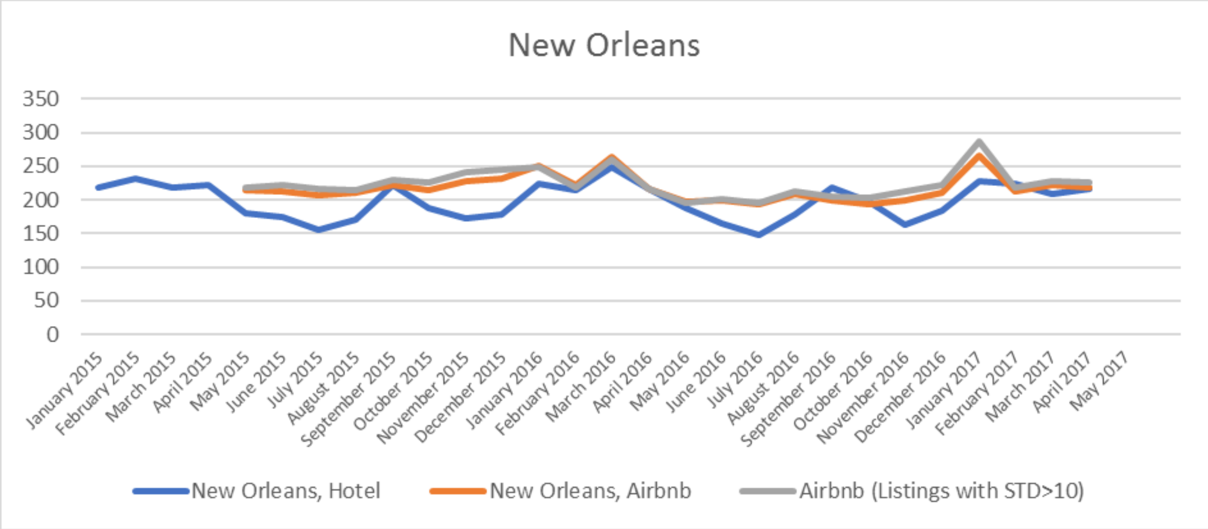
Four cities (Berlin, Paris, Barcelona & Los Angeles) show a very high polarization within the host mass, where a very small number of listings (4,79%-11,25%) reach the average Airbnb price standard deviation or overall (4,79% - 31,18%). Similarly, a minority of hosts reach the levels of price variation that hotels boast (3,9% - 37,81%). This means that the majority vary their prices very little in these cities compared to the few who list their properties often and adjust their prices based on their expectation of demand. When you examine the four locations Berlin has the highest percentage of listings that are booked for under 90 days per year (72,5%) while the other three are among the locations more often booking their listings for 90 days or more. Therefore, the previously considered learning curve effect is not persistent in all locations, or the hosts in different locations have divergent attitudes towards using Airbnb and participating in sharing economy.

4.4 High-level comparison between hotels and Airbnb

Based on the graphs derived from Airbnb pricing data and the visualized hotel price indices, one can determine the following conclusions. Airbnb users on average do not adjust their pricing as intensely as hotels do based on demand fluctuations. Although some similarities can be discerned from the graphs for example in New Orleans in spring 2016 where both hotels and Airbnb prices converge with similar intensity – and reaching similar price range. Another noteworthy aspect can be discerned from the distance between the two graphs from each other on the Y-axis: Airbnb accommodation is not priced as aggressively in some locations. This can indicate two things: 1) there are listings in the data set that skew the result, 2) certain locations around the world undercut hotel prices more aggressively than elsewhere. Of the twelve locations six cities show average hotel price and Airbnb price graphs that intersect in one or more time periods.

Based on the findings detailed in section 4.3 there exists a considerable portion of users that are somewhat passive in adjusting their pricing within a month, and a small portion that are highly aggressive in their pricing (around 2% adjust their prices within a month with a standard deviation of 50 or higher in Amsterdam, i.e. 50 euros). To examine this further a third line is added to the graph, which disregards the listings that have a small price standard deviation (between zero and ten). Overall this seems to have a minor effect in most cities on the intensity that the revenue management of Airbnb compares to hotel accommodation.




New Orleans
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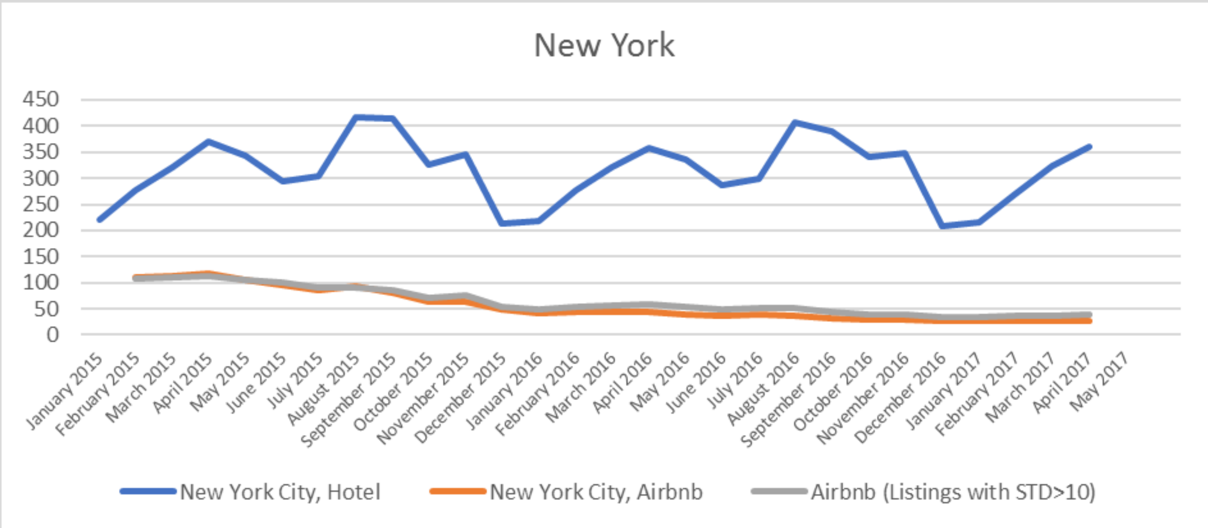
New Orleans, Hotel
New Orleans, Airbnb
Airbnb (Listings with STD>10)


New York
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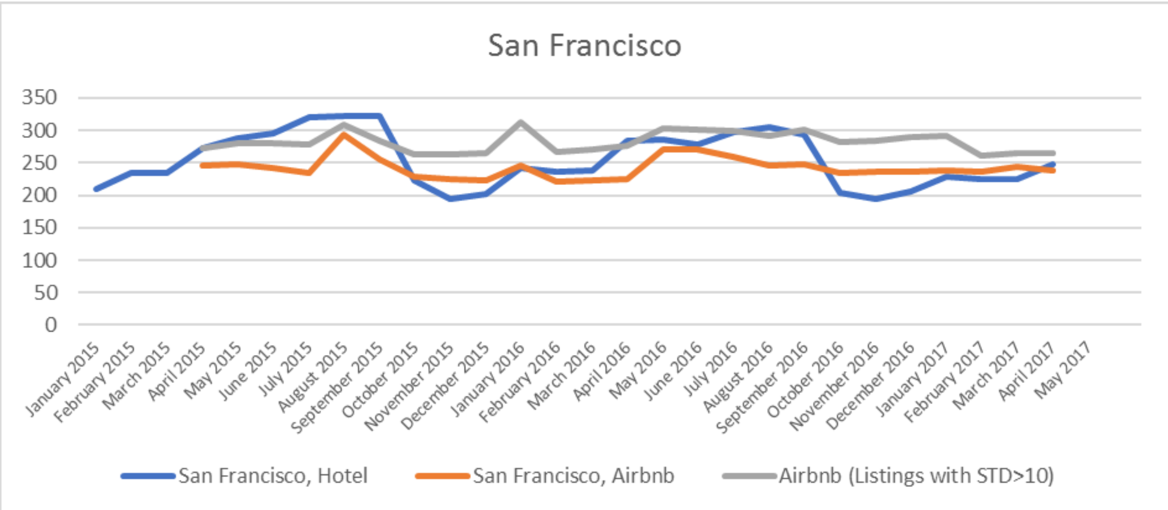
New York City, Hotel
New York City, Airbnb
Airbnb (Listings with STD>10)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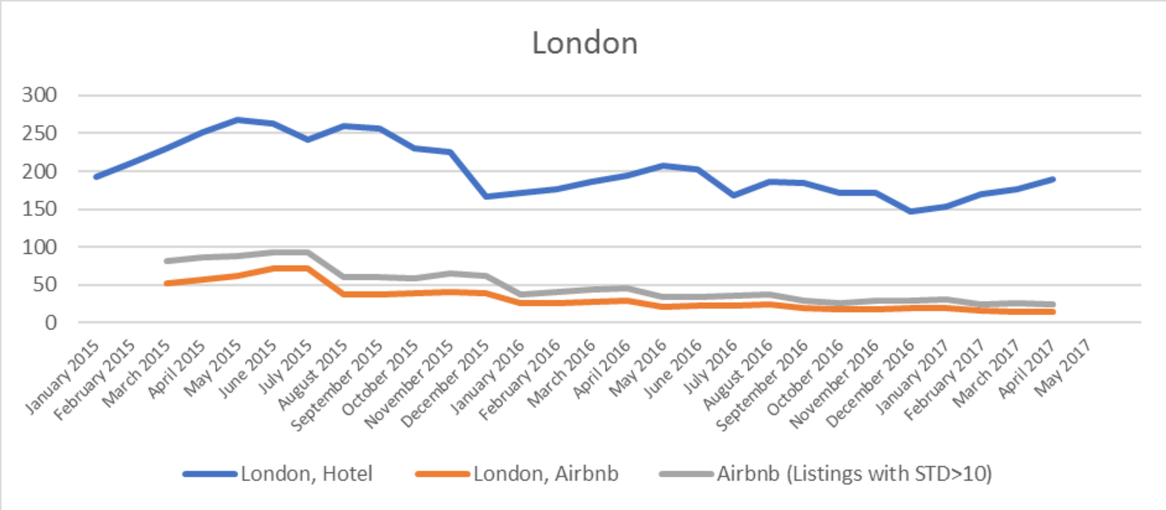
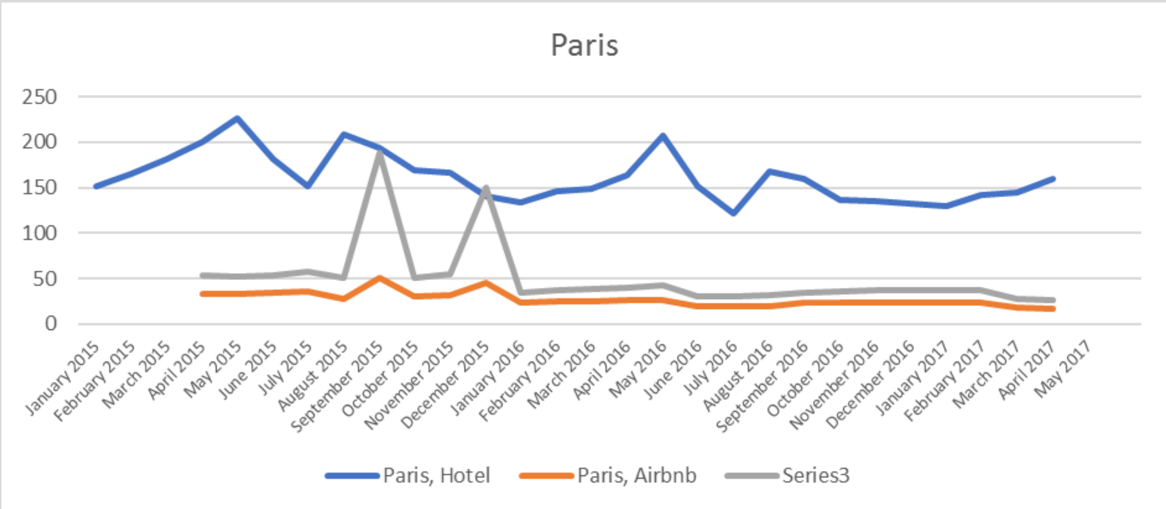
San Francisco, Hotel
San Francisco, Airbnb
Airbnb (Listings with STD>10)





Figures 8. Detailing the differences in price variation between hotels and Airbnb accommodation. Average price of accommodation in hotel or Airbnb

While the focus of this research is not to ascertain which is cheaper in each city – hotel or Airbnb – the figures on the previous page indicate very divergent practices between the cities. Hotel accommodation in New York is vastly undercut in Airbnb prices by a margin of 100 dollars a night or more. Possible reasons can be that hotels are enjoying huge premiums in these locations either to boost their profits or to cover their costs, which causes their prices to be high. Alternatively, Airbnb is engaging in aggressive pricing by giving low pricing tips that the hosts follow accordingly, or the Airbnb locations are most often outside the most expensive areas which brings down the prices considerably. When examining the Airbnb average price graph in London, New York and Paris; all three indicate a downward trend in overall prices and a possible explanation can be that Airbnb wishes to push prices down with cheap price tips or that the hosts are competing heavily against each other in these locations which drives the prices down.

It can be noted, however, that Airbnb accommodation prices have some correlation with the pricing trends that hotels have. This serves to indicate that they follow the same demand patterns, although the magnitude that Airbnb hosts adjust their pricing is lower. When comparing the two Airbnb price lines, the line indicating the average price of hosts that have a yearly price standard deviation above ten euros / dollars remains consistently above the line averaging the entire data set. This indicates that hosts that adjust their prices more, also appear to charge more for the stay at their apartment.

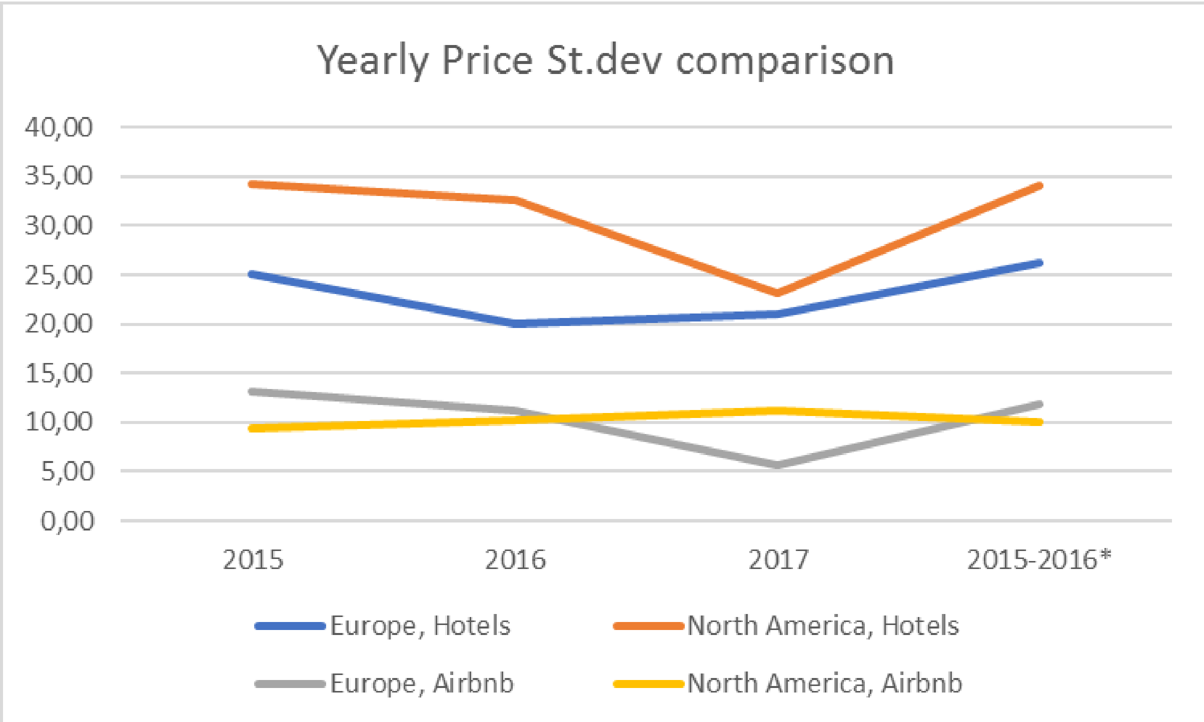


Figure 9. Comparison of average price deviation between hotels and Airbnb aggregated for comparison between Europe (Amsterdam, Barcelona, Berlin, London & Paris) and North America (New Orleans, New York, Los Angeles, San Francisco & Toronto)

By aggregating data from the five cities in Europe and the five cities in North America we can arrive at two conclusions: 1) hotels in America show a higher variance in prices during the year than in European hotels and 2) this gap is smaller when comparing Airbnb accommodation in Europe and North America.

4.5 Discussion

In this chapter I will engage in discussion based on the findings in the previous four sections and provide answers to my research questions based on the empirical study. I will also discuss the limitations of the study scope and possible avenues for future research.

What can be discerned from identifiable trends between Airbnb pricing and hotel pricing?

Pricing trends affecting Airbnb listings prices indicate considerable city-specific variability and the study findings suggest similarity in terms of demand spikes. However, by examining cities such as London, New York and Paris and the low price-levels compared to the hotel price index the large gap begs the question: is Airbnb settings the price suggestions that hosts receive too low? This question has two interesting sides to it. Firstly, hosts that follow the suggestion set their prices too low and miss out on additional income that they could receive – even without performing yield management. Subsequently this causes the profits of hosts that set prices more accordingly to plummet as their prices are undercut by their Airbnb competitors which underscores the high rivalry classification posited for Airbnb by Constantiou et al. (2017). Secondly, it bears similarity to predatory pricing which is discussed in section 2.3.4. If the hosts are accommodating guests at minimal costs or maybe even below costs (hosts may not consider the opportunity costs for the time they spend), this highlights the uneven playing field between traditional hotels and hostels that face different regulatory standards and associated cost overheads.

As discussed in section 4.2 the generally accepted notion that booking early in advance of your trip saves money in accommodation and flights. However, as is observable in the case of New York this does not hold as on average the price of stay falls in the last month(s) before the stay. A possible cause for this is that hosts that list their properties occasionally in Airbnb do not know their schedules several months in advance and list it as a last-minute option for travelers looking for budget options. The host may wish to get some extra money from their apartment should they be away from the city during the time of the stay and may settle for a smaller compensation than what is obtainable. Another possibility is that last-minute options do not get fully booked, therefore travelers have the opportunity to choose the cheapest options. Considerations by Gibbs et al. (2016) are divergent to these findings as the researchers posited that occasional users would charge higher prices and vet their guests to offset the risk of Airbnb hosting. Further research could be conducted on the booking patterns: when do listings get booked and how far in advance and examine this phenomenon in further locations.

Based on Airbnb rental booking and price data, how common is it for hosts to perform revenue management?

By comparing the data derived from Trivago hotel price indices to the standard deviations achieved from Airbnb booking data we can come to the following conclusions: majority of hosts fall far short of the levels of revenue management that hotels do. Of the cities in the study New Orleans shows the lowest polarization between host with around third of the hosts reaching the average hotel price standard deviation. The other eleven cities fall in the range 3,9% and 23,5% which indicates that very few hosts perform revenue management and yield pricing that is comparable to hotels in magnitude.

The implications of this should not be disregarded for future entrepreneurs and businesses seeking to implement a business model that is dependent on the individual setting the price on what they offer on a sharing economy platform (commercial sharing system). A business and individual misses out on profits that they could receive should they have sufficient support and knowledge of appropriate pricing. This of course is assuming that the Airbnb host is interested in maximizing their gain from their short-term rentals. As is observable in Table 11, hosts that rent their apartment out more during the year adjust their prices more actively than those who do not. This implies learning curve effects in price setting, but is also a consideration of time management: how much time is a host willing to put into managing their property on Airbnb. As discussed in my research, this extra effort to manage properties on Airbnb more effectively has created a business gap for entities such as Guesty and Beyond Pricing that enable Airbnb hosts to adjust their pricing more conveniently.

Considering the regulatory details of the cities collected in Table 13, should Airbnb hosts be running an active business in their home &/ extra apartment(s)? If active revenue management can be considered an indicator of running a business in your apartment, this would then indicate that most people do not perform at that level at least – even if they intend to. As I discussed in the chapter 4.3 and showed in Figure 7, the trend shows that Airbnb hosts are picking up speed on the revenue management side of things. Airbnb hosts should be aware of the limitations that regulation sets on their rentals and applicable taxation practices to avoid legal percussions, whether they perform active revenue management or not.

What differences can be discerned from host pricing practices, and how does it relate to previous research into sharing willingness?

Considering the research into Airbnb price determinants by Wang & Nicolau (2017) and clustering of users by sharing motivation by Hellwig et al. (2015) it seems clear that host characteristics play a part in their capability and willingness to extract higher prices with revenue management and yield pricing. Hellwig et al. (2015) noted in their research that different user clusters had varying opinions about reciprocity and generosity. Using their user clustering (detailed in Table 1) the hosts that are least generous would belong to the groups sharing opponents and sharing pragmatists. The total proportion of these two segments was 39,5% in the study. Based on the findings in section 4.3 it can be suggested that sharing pragmatists as named by Hellwig et al. (2015) are the hosts with the highest price standard deviation, as they seek to gain monetary benefits from participating in Airbnb apartment sharing. In contrast, the user clusters sharing normatives and sharing idealists (Hellwig et al., 2015 study proportion was 60,5%) represent Airbnb hosts that consider sharing a natural thing to do, and do not expect great economic benefit from doing it. Thus, they would be less inclined to perform revenue management due to their high generosity and reciprocity.

Research by Hellwig et al. (2015) indicated varying degrees of resource scarcity, which may contribute to the varying percentages across the twelve city locations. In cities where apartment prices are high, individuals with resource scarcity may feel pressed to rent out their apartment to afford the rent. Consecutively, this may also lead to apartment scarcity due to apartment owners preferring to rent on Airbnb instead of on a monthly-basis on normal rental markets due to higher price yields reached on Airbnb. This has effect on cities such as Los Angeles that face a housing crisis in affordable housing (Lee, 2016).

Table 13: Summary of the twelve locations detailing host data characteristics

	Gap between Airbnb and hotel prices	Airbnb price std. (2016)	Hotel price std. (2016* / 2017**)	% of users reaching average price std.	% of listings reaching average hotel price std.	Percentage of Entire home/apt in listings	Percentage of Private room in listings	Percentage of Shared room in listings	Listings with < 90 bookings	Listings with > 90 bookings	Listings with > 180 bookings	Rank of Airbnb rev. man.	Rank of hotel rev. man.	Rank of polarization within host mass	Regulation on short-term rentals	Specifics of regulation
Amsterdam	Small	11,80	25,47*	30,9 %	12,6 %	78,3 %	21,3 %	0,4 %	59 %	29 %	12 %	9	5	11	yes	Maximum legal number of short-term rental nights without need for certification: 60 days Registration for short-term renting needed: No Tenant may legally rent: Primarily no
Barcelona	Small	30,95	26,92*	10,8 %	12,8 %	50,5 %	48,4 %	1,1 %	49 %	27 %	24 %	2	4	3	yes	Registration for short-term renting needed: yes Registration required for short-term rental that are under 30 days
Berlin	Small	22,77	13,42*	4,8 %	9,8 %	50,5 %	48,0 %	1,4 %	73 %	23 %	5 %	5	11	1	yes	Registration for short-term renting needed: Yes, unless renting under 50% of the apartment.
London	Large	7,96	13,11*	25,7 %	16,5 %	50,4 %	48,3 %	1,3 %	58 %	28 %	14 %	12	12	8	yes	Maximum legal number of short-term rental nights without need for certification: 90 days
Paris	Large	22,81	21,36*	5,8 %	6,4 %	85,8 %	13,1 %	1,0 %	44 %	31 %	25 %	4	8	2	yes	Registration for short-term renting needed: No, if primary residence and living there for over 4 months per year Registration required for short-term rental that are under 365 days if previous condition does not apply
Melbourne	Small	11,31	24,78**	28,1 %	13,6 %	56,7 %	40,9 %	2,5 %	53 %	29 %	18 %	10	6	10	no	Tenant may legally rent: No
Sydney	Small	20,20	17,00**	24,7 %	23,5 %	61,9 %	36,5 %	1,6 %	57 %	24 %	19 %	7	9	5	upcoming, currently disputed	
Los Angeles	Medium	28,33	15,66*	11,2 %	20,2 %	58,7 %	36,2 %	5,2 %	49 %	35 %	16 %	3	10	4	yes	Short-term rentals illegal, limit of short-term rental 30 days in some areas
New Orleans	Small	35,83	28,79*	31,2 %	37,8 %	73,5 %	25,1 %	1,4 %	50 %	30 %	20 %	1	3	12	yes	Registration for short-term renting needed: Yes Other: Cannot operate near an existing B&B
New York City	Large	14,68	57,81*	27,8 %	3,9 %	49,4 %	47,9 %	2,8 %	74 %	20 %	7 %	8	1	9	yes	Tenant may legally rent: No Short-term rentals illegal when under 30 days in length - unless the host is present
San Francisco	Small	22,54	38,69*	23,4 %	14,1 %	59,1 %	36,3 %	4,6 %	53 %	33 %	14 %	6	2	6	yes	Registration for short-term renting needed: Yes Other: If resident present, no limit to number of nights stayed. If not, maximum 90 days per year.
Toronto	Small	10,17	22,03*	24,7 %	12,6 %	63,8 %	33,6 %	2,6 %	54 %	29 %	17 %	11	7	7	no	Tenant may legally rent: Renting can be against lease terms

4.6 Theoretical and managerial implications

This research has provided new insight about the capabilities of individuals pricing their offerings in a commercial sharing system. Contradictory conclusions were reached about occasional users' approach to pricing. Considerations by Gibbs et al. (2016) are divergent to the findings in this thesis as the researchers posited that occasional users would charge higher prices and vet their guests to offset the risk of Airbnb hosting. Conclusions reached in this thesis suggest that occasional users rent their properties a short time before the calendar date and rent at a low price. Further research should be undertaken the examine the reasons for this phenomenon further and seek additional verification. Furthermore, this research used a quantitative statistical data analysis to examine revenue management, which provides a new addition to research into sharing economies.

Managers can look to this research for insight into managing and selecting their business model for sharing economy. Regulators and other decisionmakers can use the thoughts in this thesis to further policy in creating a leveled playing field, and consider the needs of traditional and disruptive industry players separately.

4.7 Limitations

I have limited the research into the hospitality industry as comparing data between industries is beyond the chosen research scope. Following this limitation in scope, the data is derived from a traditional industry player and a disruptive one. Airbnb is selected due to its leading status in the industry and will be compared to an aggregated view of hotels through a price index. For the purpose of representability, one must be aware that Airbnb caters to different travelers than hotels and the two data masses are not fully comparable. Research has indicated that business travelers are less likely to seek accommodation in Airbnb (Zervas et al, 2015). However, the supply and demand mechanics are similar between the two. My approach limits the geographical scope to some extent. By having data points from North America, Europe and Australia, this research avoids focusing on just one region and one culture. However, all locations are Western developed countries and all cities in the sample are major cities. Asian cultures and smaller locations are omitted from the study. Including smaller locations could provide locations that demonstrate a younger phase in Airbnb adoption and the service lifecycle, but could also provide a less perfect sample compared to a city such as Paris with some 56 000 listings available for analysis.

5 Conclusion

This research sought to examine the extent at which individuals are equipped to perform revenue management and thus perform on-par with the hotels in the hospitality industry. Through a combination of empirical data analysis and previous research into pricing and sharing motivations, this research was able to shed light into the unresearched phenomenon and provide theoretical and managerial contribution for future purposes. This research identified phenomena that would merit further research – both quantitative and qualitative in nature. Furthermore, should future business models be dependent on individuals pricing their own offering, considerations should be made not only from the view of the viability of the business for the individual and platform provider, but also the regulatory aspects to avoid unleveled playing fields and predatory pricing.

6 References

Akbar, P., Mai, R. and Hoffmann, S. (2016). When do materialistic consumers join commercial sharing systems. Journal of Business Research, 69(10), 4215-4224.

Baker, T. & Collier D. (1999). A comparative revenue analysis of hotel yield management heuristics. Decision sciences, 30, 239-263.

Belk, R. (1988). Possessions and the Extended Self. Journal of Consumer Research, 15, 139-168.

Belk, R. (2013). Extended self in a digital world. Journal of Consumer Research, 40(3), 477-500.

Belk, R. (2014). You are what you can access: Sharing and collaborative consumption online. Journal of Business Research, 67, 1595-1600.

Belobaba, P. (1987). Air travel demand and airline seat inventory management, PhD, Massachusetts Institute of Technology, Cambridge.

Boyd, E. & Bilegan, I. (2003). Revenue Management and E-Commerce. Management Science, 49(10), 1363-1386.

Broderick, M. (2015). What's the Price Now? Communications of the ACM, (58), 21-23.

Cohen, B. & Kietzmann, J. (2014). Ride On! Mobility Business Models for the Sharing Economy. Organization & Environment, 27(3), 279-296.

Constantiou, I., Marton, A. & Tuunainen, V. (2017). Of Franchisers and Principals, Chaperones and Gardeners. The Four Models of the Sharing Economy. MIS Quarterly Executive, December 2017 (forthcoming).

Cusumano, M. (2015). How Traditional Firms Must Compete in the Sharing Economy. Communications of the ACM, (58(1), 32-34.

Eisenhardt, K. (1989). Building theories from case study research. Academy of Management Review, 14(4), 532-550.

Gibbs, C., Guttentag, D., Gretzel, U., Morton, J., & Goodwill, A. (2017). Pricing in the sharing economy: a hedonic pricing model applied to Airbnb listings. Journal of Travel & Tourism Marketing, 1-11.

Hellwig, K., Morhart, F., Girardin, F. & Hauser, M. (2015). Exploring different types of sharing: A proposed segmentation of the market for "sharing" businesses. Psychology & Marketing, 32(9), 891-906.

Huefner, R. J. (2015). The sharing economy: Implications for revenue management. Journal of Revenue and Pricing Management, 14(4), 296-298.

Kung, L. & Zhong, G. (2017). The optimal pricing strategy for two-sided platform delivery in the sharing economy. Transportation Research Part E 101, 1-12.

Krämer, F., Schmidt, K., Spann, M. and Stich, L. (2017). Delegating pricing power to customers: Pay What You Want or Name Your Own Price? Journal of Economic Behavior & Organization, 136, 125-140.

Lamberton, C. & Rose, R. (2012). When is ours better than mine? A framework for understanding and altering participation in commercial sharing systems. Journal of Marketing, 76, 109-125.

Lee, D. (2016) How Airbnb Short-Term Rentals Exacerbate Los Angeles's Affordable Housing Crisis: Analysis and Policy Recommendations. Harvard Law & Policy Review, 10, 229-253.

Littlewood, K. (2005). Forecasting and control of passenger bookings. Journal of Revenue and Pricing Management, 4(2), 111-123.

Malhotra, A. & Van Alstyne, M. (2014). Economic and Business Dimensions The Dark

Side of the Sharing Economy and How to Lighten It. Communications of the ACM, 57(11), 24-27.

Martin, C. (2016). The sharing economy: A pathway to sustainability or a nightmarish form of neoliberal capitalism? Ecological Economics, 121, 149-159.

Martin, C., Upham, P. and Budd, L. (2015). Commercial orientation in grassroots social innovation: Insights from the sharing economy. Ecological Economics, 118, 240-251.

McAfee, A. & Brynjolfsson, E. (2016) Human Work in the Robotic Future, Foreign Affairs, July/August, 139-150.

Meredith, J. (1998). Building operations management theory through case and field research. Journal of Operations Management, 16(4), 441-454.

Mims, C. (2015). How Everyone Misjudges the 'Sharing' Economy. Wall Street Journal.

Morrison, S. (2010). Priceline Shifts Model in Asia - Fixed-Price Bookings Grow Abroad, Where Name-Your-Own-Price Doesn't Fly. Wall Street Journal.

Niels, G. & Ten Kate, A. (2000). Predatory Pricing Standards: Is There a Growing International Consensus? The Antitrust Bulletin, 45(3), pp.787-809.

Ozanne, L. K., & Ballantine, P. W. (2010). Sharing as a form of anti-consumption? An examination of toy library users. Journal of Consumer Behaviour, 9(6), 485-498.

Perakis, G. & Sood, A. (2006). Competitive Multi-period Pricing for Perishable Products: A Robust Optimization Approach. Math. Program., Ser. B 107, 295-335.

Philip, H, E., Ozanne, L. K., & Ballantine, P. W. (2015). Examining temporary disposition and acquisition in peer-to-peer renting. Journal of Marketing Management, 31(11-12), 1310-1332.

Richardson, L. (2015). Performing the sharing economy. Geoforum, 67, 121-129.

Scheepens, A., Vogländer, J. & Brezet, J. (2016). Two life cycle assessment (LCA) based methods to analyse and design complex (regional) circular economy systems. Case: making water tourism more sustainable. Journal of Cleaner Production, 114, 257-268.

Steinmetz, K. (2015). Airbnb Hosts Never Have to Set Their Own Price Again. Time.com.

Wang, D. & Nicolau, J. (2017) Price determinants of sharing economy based accommodation rental: A study of listings from 33 cities on Airbnb.com. International Journal of Hospitality Management, 62, 120-131.

Yeoman, I. & McMahon-Beattie, U. (2017). The turning points of revenue management: a brief history of future evolution. Journal of Tourism Futures, 3(1), 66-72.

Zervas, G., Byers, J. & Proserpio, D (2014). The Rise of the Sharing Economy: Estimating the Impact of Airbnb on the Hotel Industry. SSRN Electronic Journal.

Books

Behrendt, S., Jasch, C., Kortman, J., Hrauda, G., Pfitzner, R. & Velte, D. (2003). Eco-service development: Reinventing supply and demand in the European Union. Sheffield: Greenleaf Publishing.

Botsman, R., & Rogers, R. (2010.) What's mine is yours: The rise of collaborative consumption online. New York: Harper.

Glaser, B. & Strauss, A. (1967). The discovery of grounded theory: strategies in qualitative research. Wiedenfeld and Nicolson, London.

Stephany, A. (2015). The Business of Sharing: Collaborative Consumption and Making it in the New Sharing Economy. Palgrave Macmillan, Houndmills, Basingstoke, Hampshire. New York, NY.

Vogtländer, J., Mestre, A., Van der Helm, R., Scheepens, A & Wever, R. (2014). Eco-efficient Value Creation. Sustainable Strategies for the Circular Economy. VSSD, Delft, the Netherlands.

Yin, R. (2009). Case study research: design and methods. Fourth edition.

Online sources

ABC News. (2017) New South Wales considers new rules for short-term rental hosts. http://www.abc.net.au/news/2017-07-21/nsw-considers-new-rules-for-short-term-rental-hosts/8730986

Airbnb. (2015). Accessed September 11th, 2017. http://blog.atairbnb.com/using-data-to-help-set-your-price/

Airbnb Community Center. (2016-2017). Ridiculous price tips. Accessed September 11th, 2017. https://community.withairbnb.com/t5/Hosting/ridiculous-price-tips/td-p/48793

Airbnb vs Berlin. Information about legal cases against Airbnb and legality of short-term rentals in the city and elsewhere in Germany. http://www.airbnbvsberlin.com/

Guardian. (2016). Berlin ban on Airbnb on short-term rentals upheld in city court https://www.theguardian.com/technology/2016/jun/08/berlin-ban-airbnb-short-term-rentals-upheld-city-court

Insideairbnb.com. Insideairbnb city-specific information on Airbnb legality. Insideairbnb.com

Karmin, C. (2015). Airbnb Crimps Hotels' Power on Pricing; Lodging listings surged for pope's U.S. visit, challenging hotel industry. Wall Street Journal (online).

Lu, V. (2015). Airbnb’s place among traditional hotels still up for debate. The Toronto Star. https://www.thestar.com/business/2015/03/04/airbnbs-place-among-traditional-hotels-still-up-for-debate.html

Maaseudun tulevaisuus. (2017). Professori: "Valion holtittomat sähköpostit tulivat kalliiksi – ilman niitä kilpailuvirasto olisi ollut hampaaton" http://www.maaseuduntulevaisuus.fi/talous/professori-valion-holtittomat-s%C3%A4hk%C3%B6postit-tulivat-kalliiksi-ilman-niit%C3%A4-kilpailuvirasto-olisi-ollut-hampaaton-1.174846

MacMillan, D. and Karmin, C. (2014). WSJ.D Technology: New York's Supreme Court Hosts Airbnb Case. Wall Street Journal (online).

Morozov, E. (2013). The “sharing economy” undermines workers’ rights. The Financial Times. https://www.ft.com/content/92c3021c-34c2-11e3-8148-00144feab7de

New York Times. (2017a). Is it time to break up Google? Accessed October 9th, 2017. https://www.nytimes.com/2017/04/22/opinion/sunday/is-it-time-to-break-up-google.html

New York Times. (2017b). How to host on Airbnb legally? https://www.nytimes.com/2017/04/07/realestate/how-to-host-on-airbnb-legally.html

PwC. (2014). The sharing economy: How will it disrupt your business? Megatrends: The collisions. http://pwc.blogs.com/files/sharing-economy-final_0814.pdf

Talouselämä.fi. (2016). Edessä todennäköisesti vuosien käräjäkierre – Talouselämän toissavuotinen juttu Valion ja Arlan väännöstä kertoo, mistä maitosodassa on kyse. Accessed October 9th, 2017. https://www.talouselama.fi/uutiset/edessa-todennakoisesti-vuosien-karajakierre--talouselaman-toissavuotinen-juttu-valion-ja-arlan-vaannosta-kertoo-mista-maitosodassa-on-kyse/f08b0da0-3a1e-317e-9e9f-55f942914a74

Techcrunch. (2015). How Much Should You Charge For Your Airbnb? Beyond Pricing Scores $1.5M To Tell You. Accessed September 12th, 2017. https://techcrunch.com/2015/03/26/best-airbnb-price/

Trivago Hotel Price indices (2015-2017). https://company.trivago.fi/thpi/, http://company.trivago.com/thpi/, http://company.trivago.de/thpi/

Yle.fi. (2016) Valiolle 70 miljoonan euron rapsut markkina-aseman väärinkäytöstä. Accessed October 9th, 2017. https://yle.fi/uutiset/3-9377304

7 Appendix

7.1 Appendix A – Visualizations, data tables and charts

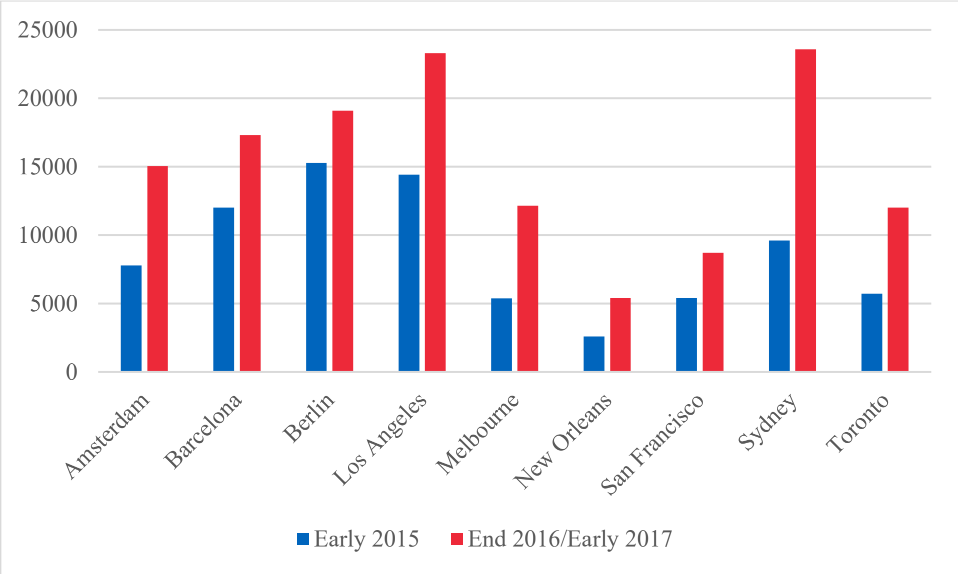
Tables A1: Tables detailing number of Airbnb listings and visualizing the growth of specific categories from 2015.

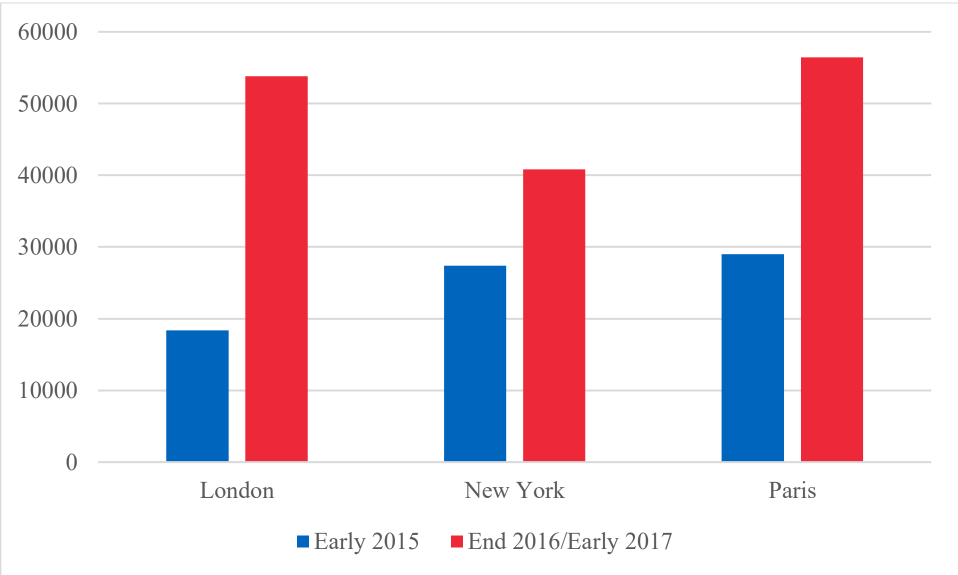
	Entire home/apt	Private room	Shared room	Total (end 2016/early 2017)
Amsterdam	78 %	21 %	0 %	15052
Barcelona	50 %	48 %	1 %	17318
Berlin	51 %	48 %	1 %	19102
Los Angeles	59 %	36 %	5 %	23309
Melbourne	57 %	41 %	2 %	12154
New Orleans	73 %	25 %	1 %	5399
San Francisco	59 %	39 %	2 %	8709
Sydney	62 %	36 %	2 %	23574
Toronto	63 %	34 %	3 %	12003

	Entire home/apt	Private room	Shared room	Total (early 2015)
Amsterdam	81 %	19 %	1 %	7785
Barcelona	59 %	41 %	0 %	12006
Berlin	61 %	38 %	1 %	15276
Los Angeles	60 %	36 %	4 %	14416
Melbourne	52 %	46 %	3 %	5375
New Orleans	68 %	31 %	2 %	2597
San Francisco	59 %	36 %	5 %	5405
Sydney	59 %	39 %	1 %	9611
Toronto	64 %	34 %	3 %	5731

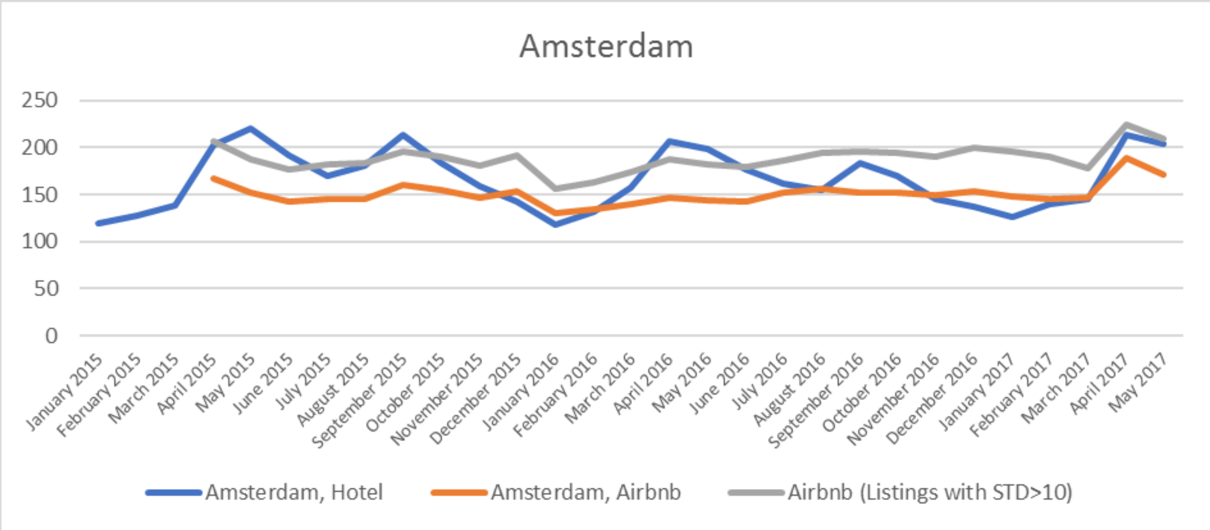
				Total (end 2016/early 2017)
London	50 %	48 %	1 %	53831
New York	49 %	48 %	3 %	40804
Paris	86 %	13 %	1 %	56430
				Total (early 2015)
London	52 %	46 %	2 %	18363
New York	58 %	39 %	3 %	27391
Paris	84 %	15 %	1 %	29012

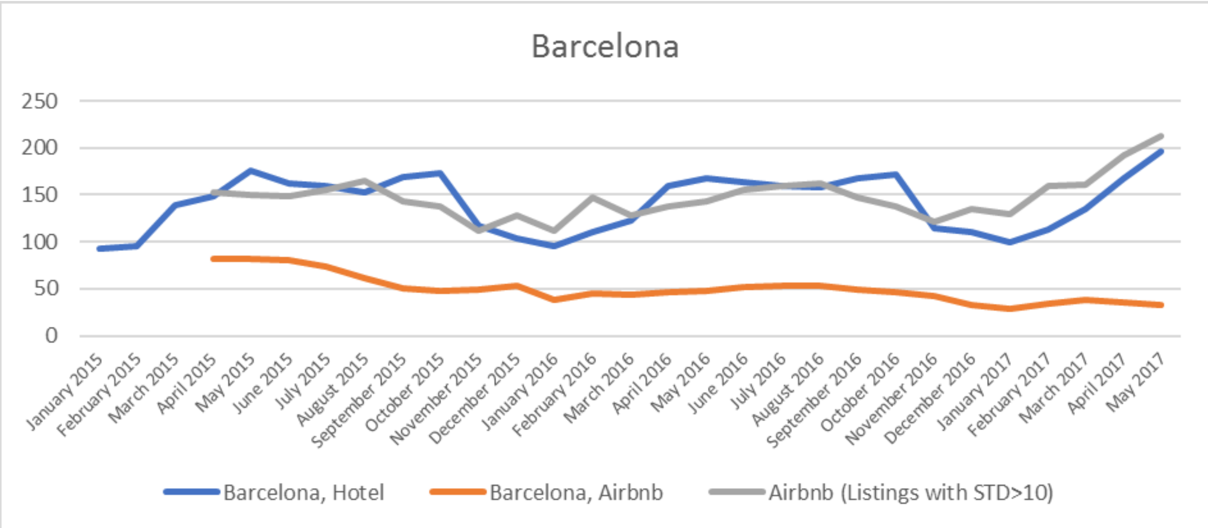
Graphs A2: Graphs visualizing the different expansion rate of Airbnb in different cities

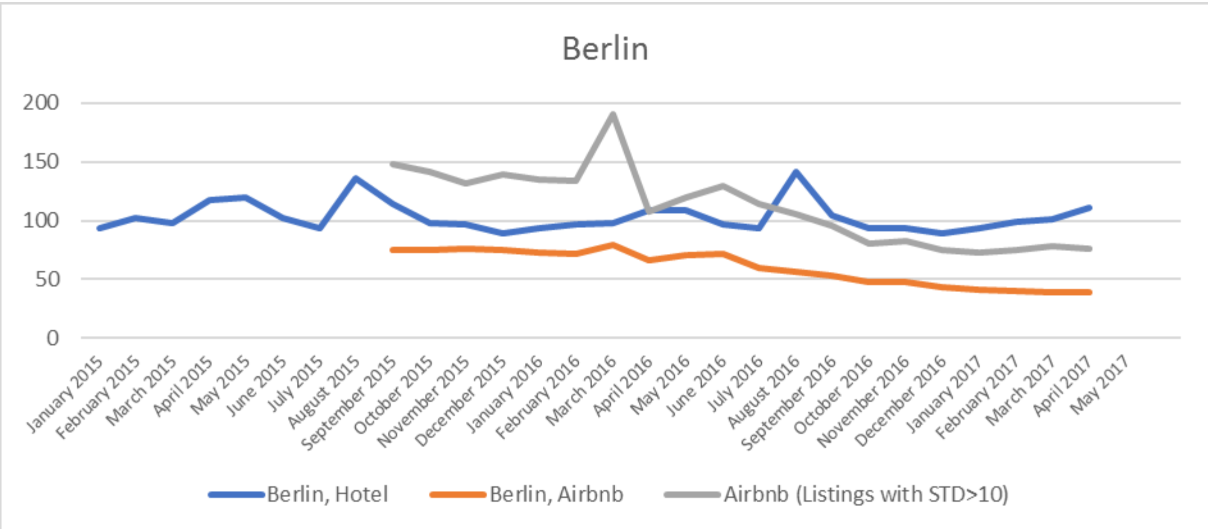


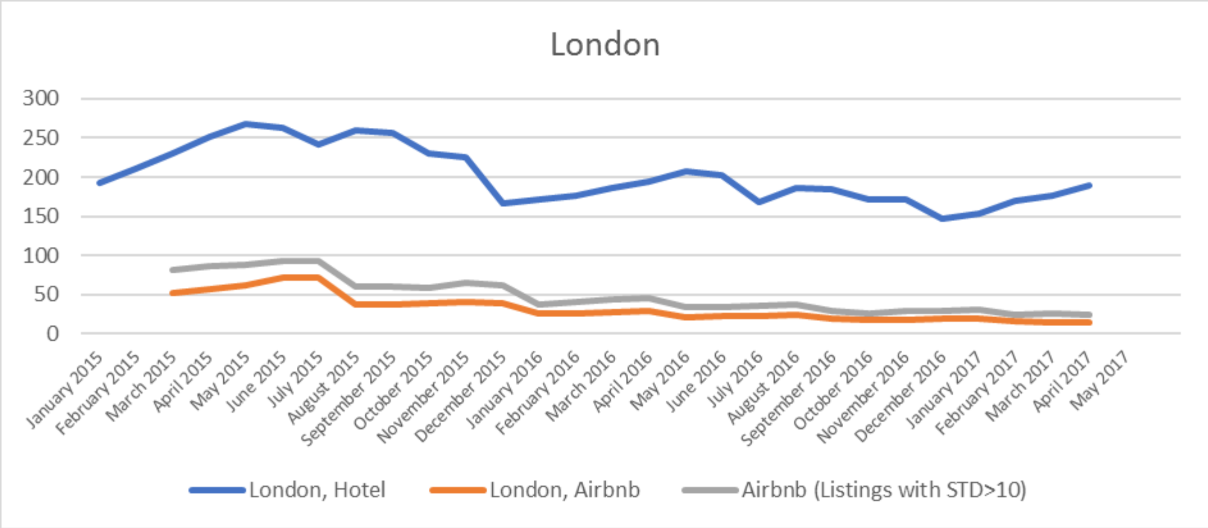


Graphs A3: Graphs visualizing the difference in revenue management magnitude between Airbnb and hotel accommodation across different locations





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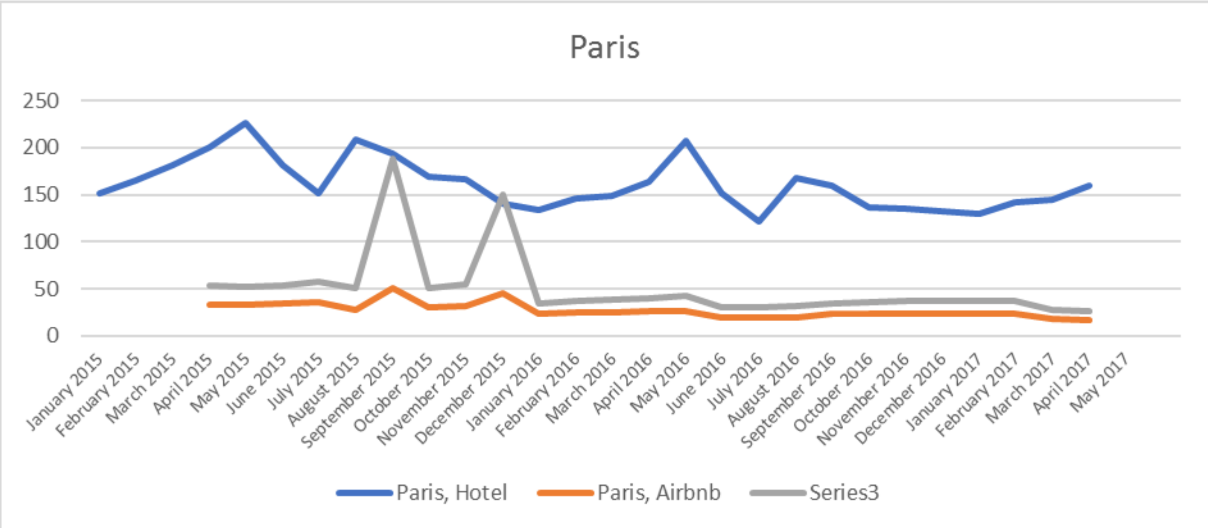
March 2017
April 2017
May 2017
London, Hotel
London, Airbnb
Airbnb (Listings with STD>10)


Paris
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January 2015
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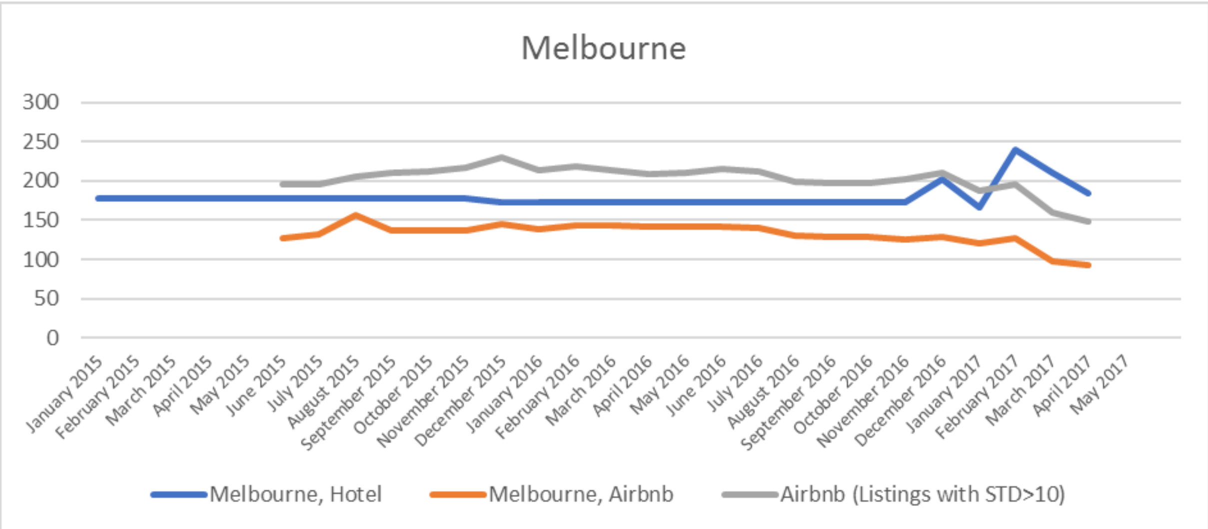
Paris, Hotel
Paris, Airbnb
Series3


Melbourne
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January 2015
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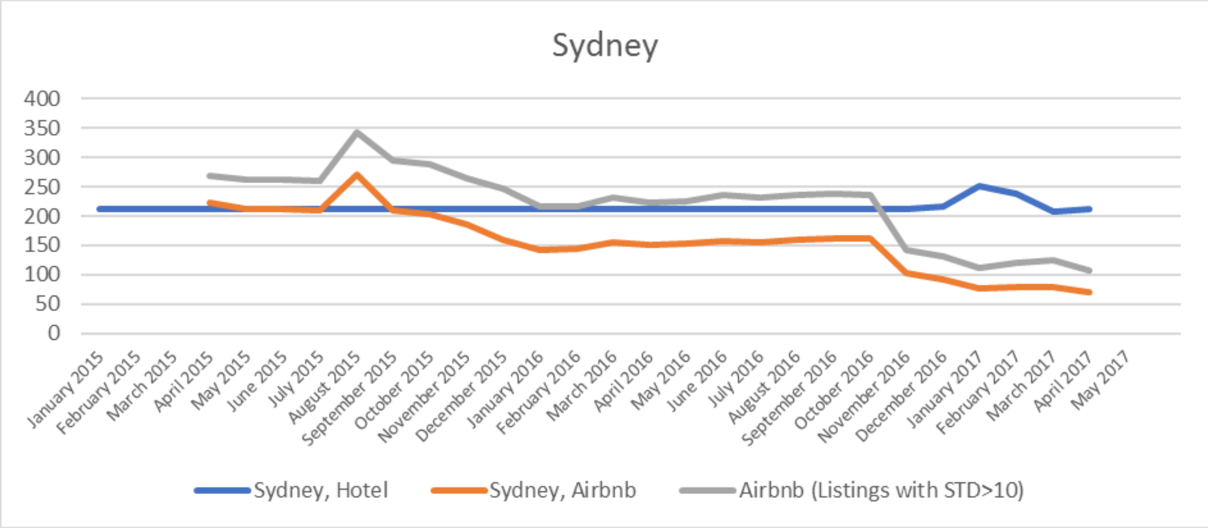
May 2017
Melbourne, Hotel
Melbourne, Airbnb
Airbnb (Listings with STD>10)


Sydney
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January 2015
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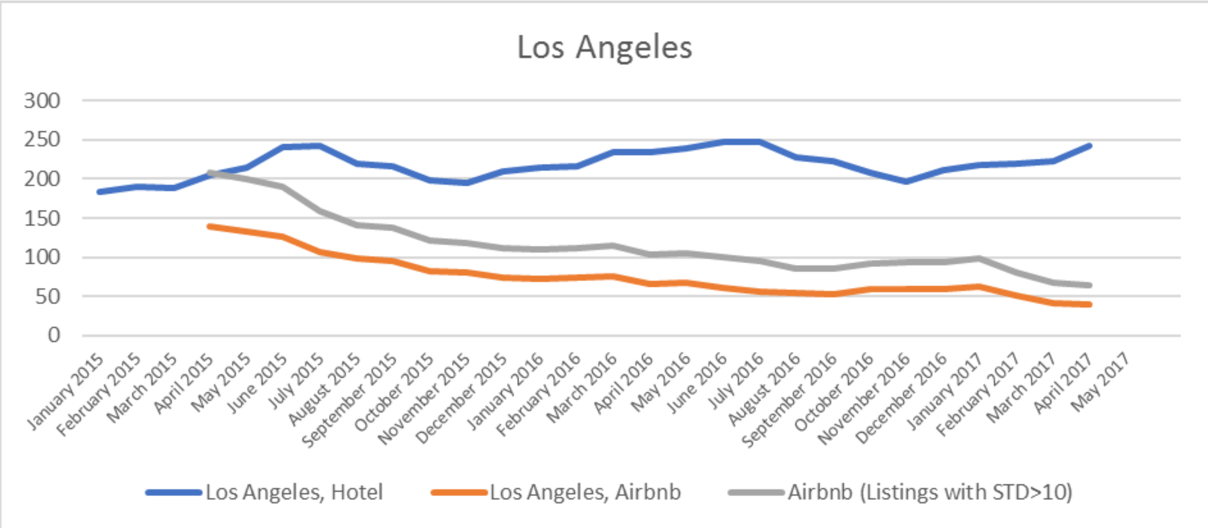
April 2017
May 2017
Sydney, Hotel
Sydney, Airbnb
Airbnb (Listings with STD>10)


Los Angeles
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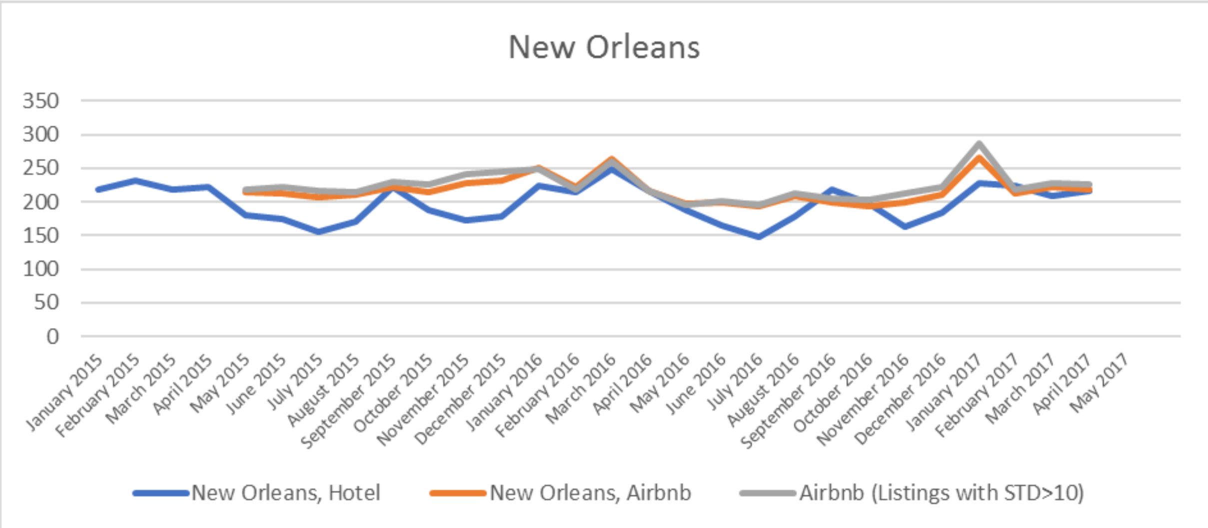
December 2016
January 2017
February 2017
March 2017
April 2017
May 2017
Los Angeles, Hotel
Los Angeles, Airbnb
Airbnb (Listings with STD>10)


New Orleans
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January 2015
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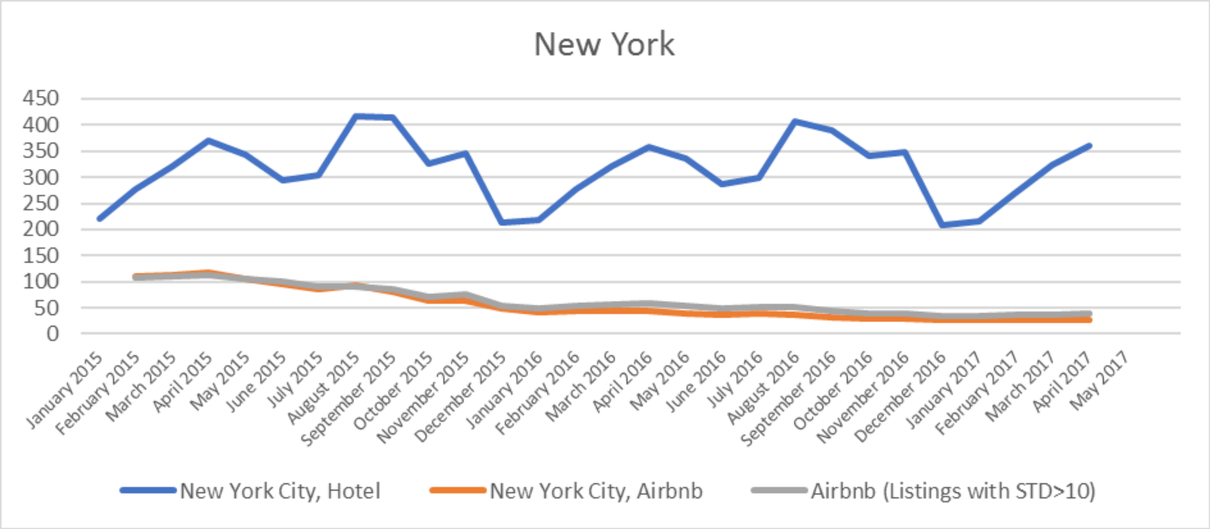
December 2016
January 2017
February 2017
March 2017
April 2017
May 2017
New Orleans, Hotel
New Orleans, Airbnb
Airbnb (Listings with STD>10)


New York
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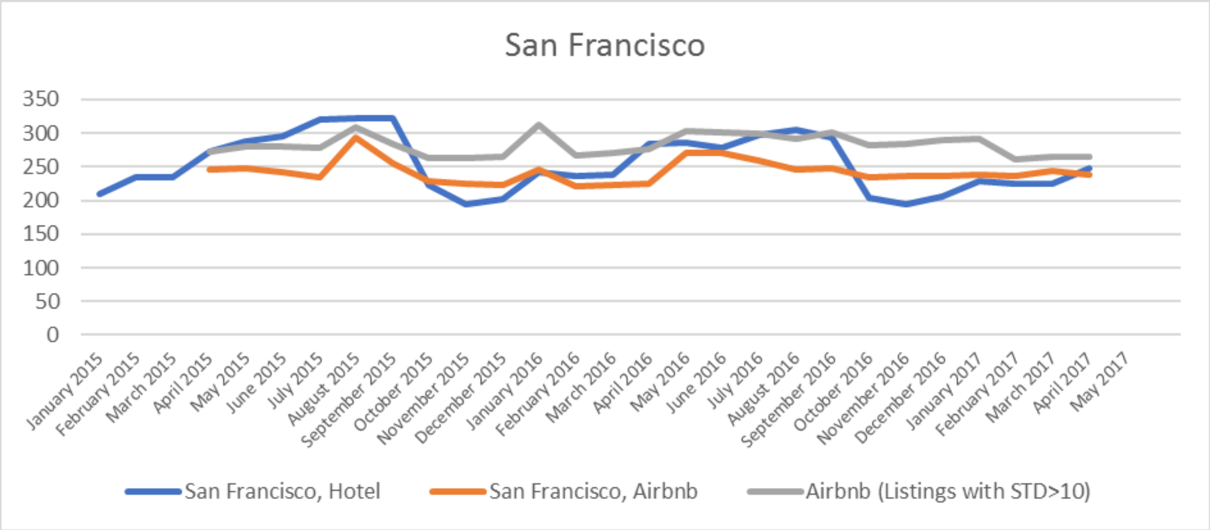
January 2017
February 2017
March 2017
April 2017
May 2017
New York City, Hotel
New York City, Airbnb
Airbnb (Listings with STD>10)


San Francisco
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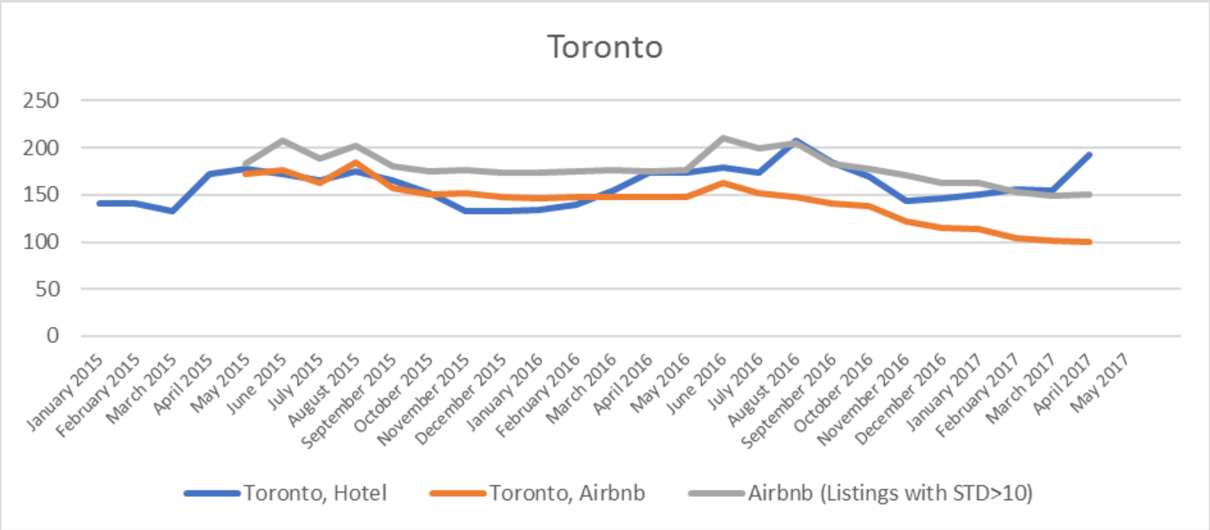
December 2016
January 2017
February 2017
March 2017
April 2017
May 2017
San Francisco, Hotel
San Francisco, Airbnb
Airbnb (Listings with STD>10)


Toronto
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November 2016
December 2016
January 2017
February 2017
March 2017
April 2017
May 2017
Toronto, Hotel
Toronto, Airbnb
Airbnb (Listings with STD>10)

Tables A4: Tables detailing the effects that number of bookings have on the intensity on revenue management (price standard deviation)

Amsterdam

ALL										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	37,90 %	29,13 %	16,46 %	7,64 %	3,43 %	2,07 %	1,11 %	0,63 %	0,39 %	1,09 %
% of 2016	34,37 %	30,35 %	17,53 %	7,71 %	3,98 %	2,14 %	1,35 %	0,74 %	0,48 %	1,21 %
% of 2017	34,58 %	32,07 %	15,89 %	7,74 %	3,52 %	2,17 %	1,22 %	0,85 %	0,50 %	1,26 %
Revenue management of listings with >90 bookings per year										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	24,12 %	33,14 %	21,41 %	9,63 %	4,69 %	2,66 %	1,55 %	1,06 %	0,57 %	1,18 %
% of 2016	26,77 %	31,72 %	19,56 %	9,19 %	4,94 %	2,41 %	1,90 %	0,98 %	0,69 %	1,83 %
% of 2017	17,92 %	38,48 %	20,16 %	9,30 %	4,82 %	2,88 %	1,90 %	1,35 %	0,87 %	2,31 %
Revenue management of listings with >180 bookings per year										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	14,64 %	30,85 %	26,17 %	12,22 %	6,59 %	3,81 %	2,08 %	1,13 %	0,95 %	1,56 %
% of 2016	15,35 %	33,19 %	24,52 %	11,70 %	5,77 %	2,77 %	2,43 %	1,42 %	1,01 %	1,82 %
% of 2017	16,06 %	37,74 %	19,45 %	10,08 %	5,72 %	3,39 %	2,18 %	1,58 %	0,94 %	2,86 %

Barcelona

ALL										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	31,97 %	39,95 %	14,20 %	6,63 %	2,82 %	1,59 %	0,96 %	0,48 %	0,39 %	0,96 %
% of 2016	38,78 %	32,31 %	11,18 %	6,45 %	3,47 %	2,32 %	1,39 %	1,25 %	0,75 %	2,05 %
% of 2017	25,78 %	34,06 %	12,80 %	7,07 %	5,45 %	3,78 %	2,51 %	1,98 %	1,47 %	5,06 %
Revenue management of listings with >90 bookings per year										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	20,47 %	43,74 %	16,17 %	9,08 %	4,15 %	2,18 %	1,25 %	0,78 %	0,61 %	1,58 %
% of 2016	25,40 %	37,68 %	13,75 %	8,59 %	4,68 %	3,07 %	1,74 %	1,67 %	0,83 %	2,59 %
% of 2017	20,29 %	33,65 %	13,81 %	8,12 %	6,44 %	4,57 %	3,03 %	2,37 %	1,85 %	5,86 %
Revenue management of listings with >180 bookings per year										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	21,81 %	51,55 %	11,59 %	6,11 %	2,55 %	2,01 %	0,36 %	1,00 %	0,46 %	2,55 %
% of 2016	23,67 %	37,82 %	14,16 %	8,99 %	4,94 %	3,21 %	1,86 %	1,77 %	0,82 %	2,75 %
% of 2017	15,38 %	31,68 %	14,24 %	9,36 %	7,61 %	5,51 %	3,80 %	3,07 %	2,21 %	7,13 %

Berlin

ALL										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	45,44 %	37,97 %	9,62 %	3,23 %	1,36 %	0,86 %	0,48 %	0,24 %	0,25 %	0,48 %
% of 2016	42,44 %	43,39 %	8,39 %	2,69 %	1,25 %	0,52 %	0,41 %	0,21 %	0,14 %	0,48 %
% of 2017	37,85 %	49,11 %	7,85 %	2,45 %	1,06 %	0,56 %	0,25 %	0,20 %	0,15 %	0,45 %
Revenue management of listings with >90 bookings per year										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	60,34 %	20,69 %	8,62 %	3,45 %	3,45 %	3,45 %	0,00 %	0,00 %	0,00 %	0,00 %
% of 2016	24,82 %	53,52 %	12,98 %	4,06 %	1,87 %	0,84 %	0,62 %	0,29 %	0,23 %	0,73 %
% of 2017	24,87 %	56,84 %	11,17 %	3,16 %	1,60 %	0,80 %	0,35 %	0,29 %	0,21 %	0,71 %
Revenue management of listings with >180 bookings per year										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015										
% of 2016	16,63 %	55,31 %	16,05 %	5,66 %	2,71 %	1,33 %	0,69 %	0,29 %	0,29 %	1,04 %
% of 2017	25,14 %	55,12 %	11,71 %	3,37 %	1,86 %	0,91 %	0,35 %	0,42 %	0,35 %	0,75 %

London

ALL										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	48,39 %	32,49 %	10,07 %	4,13 %	1,77 %	1,23 %	0,67 %	0,48 %	0,17 %	0,56 %
% of 2016	42,29 %	36,61 %	10,74 %	4,32 %	2,24 %	1,43 %	0,73 %	0,48 %	0,29 %	0,82 %
% of 2017	41,35 %	39,81 %	9,46 %	3,88 %	2,14 %	1,15 %	0,66 %	0,37 %	0,24 %	0,90 %
Revenue management of listings with >90 bookings per year										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	44,04 %	35,12 %	10,68 %	4,55 %	1,95 %	1,39 %	0,76 %	0,59 %	0,19 %	0,73 %
% of 2016	29,57 %	43,05 %	13,81 %	5,67 %	2,96 %	1,98 %	0,91 %	0,59 %	0,36 %	1,11 %
% of 2017	32,67 %	44,68 %	10,68 %	4,72 %	2,87 %	1,46 %	0,87 %	0,49 %	0,28 %	1,27 %
Revenue management of listings with >180 bookings per year										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	33,75 %	42,57 %	12,08 %	4,97 %	2,07 %	1,52 %	0,99 %	0,51 %	0,27 %	1,26 %
% of 2016	27,40 %	44,01 %	13,86 %	5,98 %	3,05 %	2,24 %	0,97 %	0,65 %	0,46 %	1,38 %
% of 2017	34,09 %	44,17 %	9,97 %	4,45 %	2,80 %	1,43 %	0,91 %	0,53 %	0,29 %	1,36 %

Los Angeles

ALL										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	40,06 %	29,05 %	14,34 %	6,22 %	2,97 %	1,96 %	1,18 %	0,78 %	0,54 %	2,86 %
% of 2016	34,61 %	35,61 %	13,43 %	5,65 %	2,87 %	2,10 %	1,06 %	0,74 %	0,61 %	3,26 %
% of 2017	32,66 %	38,35 %	12,82 %	5,45 %	2,95 %	2,05 %	1,20 %	0,95 %	0,60 %	2,95 %
Revenue management of listings with >90 bookings per year										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	25,02 %	33,22 %	18,31 %	8,16 %	3,85 %	2,77 %	1,95 %	1,26 %	0,76 %	4,69 %
% of 2016	28,39 %	37,17 %	14,99 %	6,47 %	3,37 %	2,50 %	1,32 %	0,88 %	0,73 %	4,15 %
% of 2017	23,10 %	42,19 %	14,90 %	6,30 %	3,64 %	2,53 %	1,58 %	1,21 %	0,75 %	3,78 %
Revenue management of listings with >180 bookings per year										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	36,93 %	27,68 %	14,43 %	6,83 %	2,77 %	2,36 %	1,59 %	1,24 %	0,88 %	5,30 %
% of 2016	21,82 %	37,85 %	17,46 %	7,33 %	4,04 %	3,10 %	1,60 %	1,19 %	0,94 %	4,66 %
% of 2017	23,21 %	40,91 %	15,10 %	6,49 %	3,69 %	2,58 %	1,68 %	1,33 %	0,79 %	4,21 %

Melbourne

ALL										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	44,52 %	26,48 %	12,86 %	6,52 %	3,51 %	1,99 %	1,09 %	0,83 %	0,56 %	1,44 %
% of 2016	38,74 %	30,96 %	12,65 %	6,99 %	3,64 %	2,32 %	1,45 %	1,01 %	0,59 %	1,57 %
% of 2017	33,05 %	35,52 %	13,33 %	6,74 %	3,83 %	2,63 %	1,47 %	0,91 %	0,61 %	1,86 %
Revenue management of listings with >90 bookings per year										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	34,24 %	32,27 %	15,15 %	6,51 %	4,37 %	1,92 %	1,87 %	1,12 %	0,75 %	1,81 %
% of 2016	32,50 %	35,15 %	13,77 %	7,50 %	3,83 %	2,35 %	1,63 %	1,27 %	0,52 %	1,47 %
% of 2017	27,89 %	36,47 %	14,70 %	7,86 %	4,51 %	3,08 %	1,69 %	0,96 %	0,70 %	2,15 %
Revenue management of listings with >180 bookings per year										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015										
% of 2016	28,39 %	36,84 %	14,65 %	7,92 %	4,20 %	2,78 %	1,75 %	1,46 %	0,54 %	1,46 %
% of 2017	25,55 %	35,17 %	15,97 %	8,70 %	5,01 %	3,53 %	1,86 %	1,13 %	0,83 %	2,23 %

New Orleans

ALL										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	28,10 %	17,47 %	17,71 %	12,36 %	7,29 %	4,94 %	2,35 %	1,84 %	2,11 %	5,76 %
% of 2016	17,53 %	15,91 %	17,70 %	12,06 %	8,67 %	6,89 %	4,49 %	3,62 %	2,49 %	10,54 %
% of 2017	12,88 %	15,72 %	14,56 %	12,45 %	9,19 %	6,57 %	5,02 %	4,17 %	3,45 %	15,94 %
Revenue management of listings with >90 bookings per year										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	21,88 %	16,61 %	19,63 %	13,58 %	7,94 %	5,59 %	2,87 %	2,14 %	2,87 %	6,89 %
% of 2016	7,72 %	14,45 %	20,62 %	14,81 %	10,44 %	7,88 %	5,53 %	4,26 %	2,89 %	11,39 %
% of 2017	6,54 %	15,04 %	16,21 %	13,27 %	10,28 %	6,91 %	5,42 %	4,45 %	3,97 %	17,91 %
Revenue management of listings with >180 bookings per year										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	31,30 %	15,37 %	15,65 %	12,05 %	5,12 %	5,68 %	2,35 %	1,52 %	3,88 %	7,06 %
% of 2016	6,29 %	11,81 %	20,53 %	15,77 %	10,92 %	8,92 %	5,40 %	5,14 %	2,89 %	12,32 %
% of 2017	6,78 %	13,69 %	16,29 %	13,45 %	10,27 %	7,29 %	5,20 %	4,69 %	3,94 %	18,41 %

New York

ALL										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	39,21 %	24,45 %	16,42 %	8,15 %	4,17 %	2,43 %	1,43 %	1,02 %	0,56 %	1,99 %
% of 2016	32,68 %	29,53 %	17,22 %	8,62 %	4,10 %	2,59 %	1,46 %	0,94 %	0,63 %	2,06 %
% of 2017	30,16 %	35,56 %	16,27 %	7,12 %	3,42 %	2,30 %	1,35 %	0,91 %	0,62 %	2,24 %
Revenue management of listings with >90 bookings per year										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	20,20 %	29,19 %	22,32 %	11,13 %	5,71 %	3,24 %	2,35 %	1,51 %	0,87 %	3,48 %
% of 2016	16,07 %	32,33 %	22,86 %	11,22 %	5,53 %	3,71 %	2,35 %	1,39 %	1,01 %	3,52 %
% of 2017	18,31 %	38,74 %	19,23 %	8,94 %	4,29 %	3,03 %	1,80 %	1,28 %	0,93 %	3,45 %
Revenue management of listings with >180 bookings per year										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	29,13 %	26,90 %	18,46 %	9,09 %	4,78 %	3,21 %	2,33 %	1,26 %	0,88 %	3,96 %
% of 2016	18,22 %	32,17 %	22,23 %	10,20 %	5,02 %	3,59 %	2,56 %	1,57 %	0,96 %	3,47 %
% of 2017	19,51 %	38,13 %	18,77 %	8,66 %	4,08 %	3,03 %	1,81 %	1,35 %	0,95 %	3,70 %

Paris

ALL										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	53,65 %	33,25 %	7,97 %	2,56 %	0,93 %	0,55 %	0,25 %	0,20 %	0,13 %	0,47 %
% of 2016	46,90 %	36,15 %	9,90 %	3,18 %	1,42 %	0,88 %	0,44 %	0,26 %	0,21 %	0,62 %
% of 2017	51,11 %	35,89 %	7,58 %	2,53 %	1,03 %	0,61 %	0,34 %	0,22 %	0,16 %	0,53 %
Revenue management of listings with >90 bookings per year										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	49,10 %	35,81 %	9,12 %	2,94 %	1,14 %	0,62 %	0,30 %	0,24 %	0,15 %	0,57 %
% of 2016	37,46 %	41,29 %	12,30 %	3,99 %	1,82 %	1,13 %	0,58 %	0,33 %	0,27 %	0,81 %
% of 2017	50,01 %	35,78 %	8,21 %	2,76 %	1,13 %	0,68 %	0,39 %	0,24 %	0,19 %	0,60 %
Revenue management of listings with >180 bookings per year										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	48,49 %	35,91 %	9,43 %	2,96 %	1,16 %	0,63 %	0,36 %	0,24 %	0,14 %	0,66 %
% of 2016	35,87 %	41,51 %	13,00 %	4,23 %	1,97 %	1,21 %	0,64 %	0,37 %	0,30 %	0,90 %
% of 2017	49,11 %	35,77 %	8,60 %	2,95 %	1,24 %	0,75 %	0,41 %	0,27 %	0,21 %	0,67 %

San Francisco

ALL										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	37,64 %	18,94 %	16,69 %	9,09 %	4,91 %	3,58 %	1,95 %	1,42 %	1,35 %	4,29 %
% of 2016	37,39 %	22,73 %	14,20 %	7,45 %	4,36 %	3,38 %	1,94 %	1,46 %	1,08 %	5,81 %
% of 2017	37,79 %	27,29 %	14,60 %	6,91 %	3,41 %	2,65 %	1,56 %	1,05 %	0,78 %	3,87 %
Revenue management of listings with >90 bookings per year										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	25,30 %	20,39 %	20,35 %	10,70 %	5,87 %	5,11 %	3,10 %	1,89 %	1,73 %	5,51 %
% of 2016	32,09 %	24,32 %	15,73 %	8,27 %	4,88 %	3,41 %	2,15 %	1,72 %	1,19 %	6,24 %
% of 2017	23,57 %	29,98 %	19,08 %	8,83 %	4,62 %	3,28 %	2,22 %	1,56 %	1,21 %	5,63 %
Revenue management of listings with >180 bookings per year										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	14,72 %	17,38 %	21,88 %	10,63 %	7,57 %	8,79 %	3,48 %	2,25 %	2,25 %	11,04 %
% of 2016	21,28 %	26,94 %	18,17 %	9,76 %	6,06 %	4,38 %	3,15 %	1,67 %	1,39 %	7,17 %
% of 2017	23,56 %	28,52 %	19,78 %	8,70 %	4,33 %	3,52 %	2,33 %	1,70 %	1,41 %	6,15 %

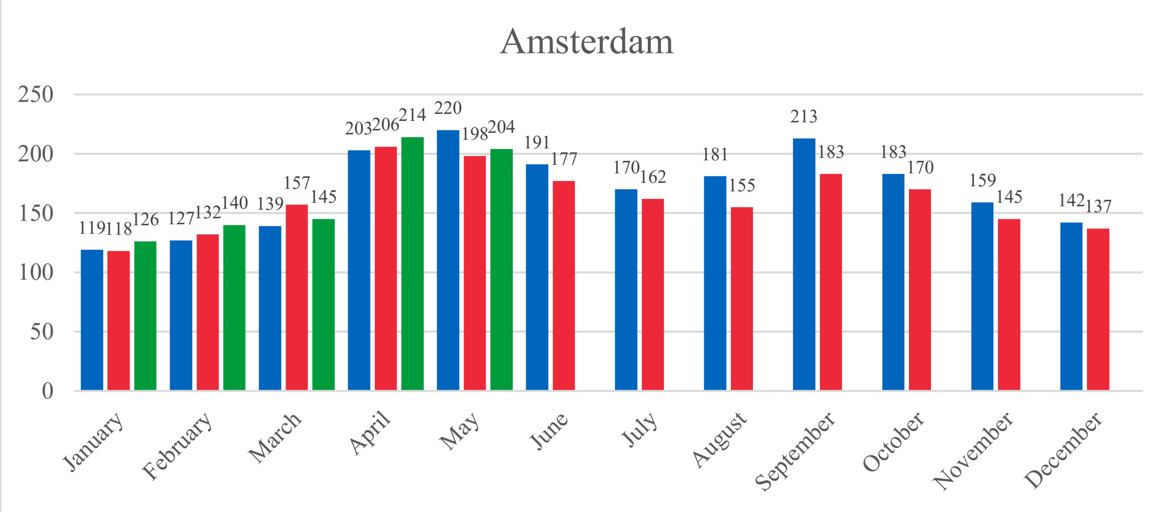
Sydney

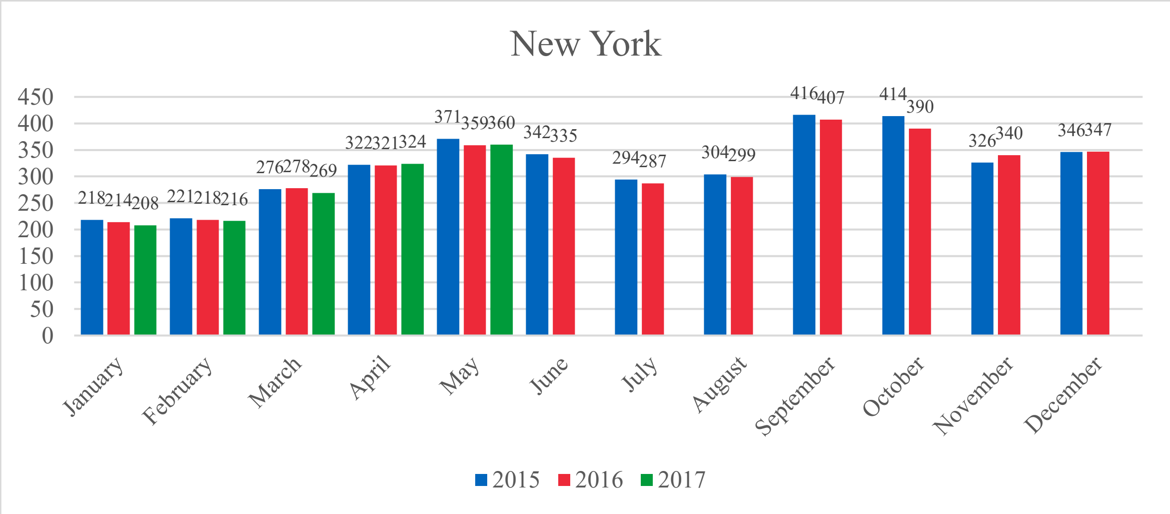
ALL										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	49,55 %	18,84 %	11,21 %	6,21 %	3,65 %	2,69 %	1,57 %	1,23 %	0,99 %	3,79 %
% of 2016	47,37 %	21,36 %	10,05 %	5,96 %	3,24 %	2,81 %	1,73 %	1,30 %	0,99 %	4,88 %
% of 2017	35,32 %	27,26 %	12,51 %	6,78 %	4,21 %	3,53 %	2,06 %	1,53 %	1,06 %	5,60 %
Revenue management of listings with >90 bookings per year										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	36,14 %	24,89 %	15,69 %	7,41 %	4,52 %	2,81 %	1,97 %	1,43 %	1,08 %	4,04 %
% of 2016	39,38 %	30,33 %	12,32 %	6,40 %	3,30 %	2,38 %	1,55 %	0,99 %	0,61 %	2,71 %
% of 2017	24,44 %	31,65 %	15,36 %	8,07 %	5,06 %	3,96 %	2,36 %	1,89 %	1,20 %	5,98 %
Revenue management of listings with >180 bookings per year										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	32,60 %	22,31 %	15,71 %	7,70 %	5,50 %	3,77 %	2,75 %	1,89 %	1,49 %	6,28 %
% of 2016	38,07 %	31,43 %	12,42 %	6,50 %	3,34 %	2,49 %	1,61 %	1,01 %	0,63 %	2,49 %
% of 2017	25,10 %	29,41 %	15,66 %	8,13 %	5,40 %	4,03 %	2,57 %	2,00 %	1,27 %	6,43 %

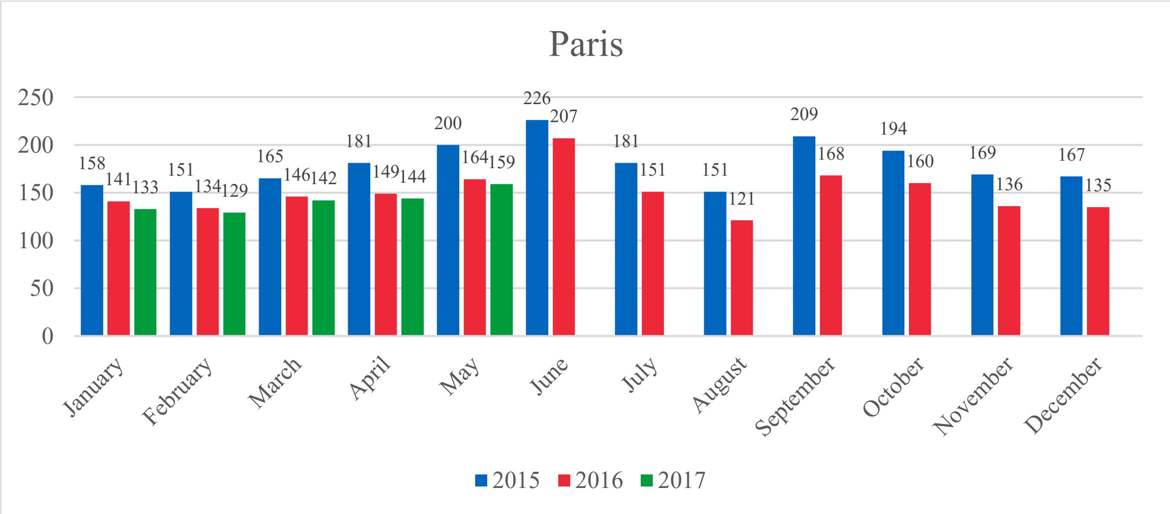
Toronto

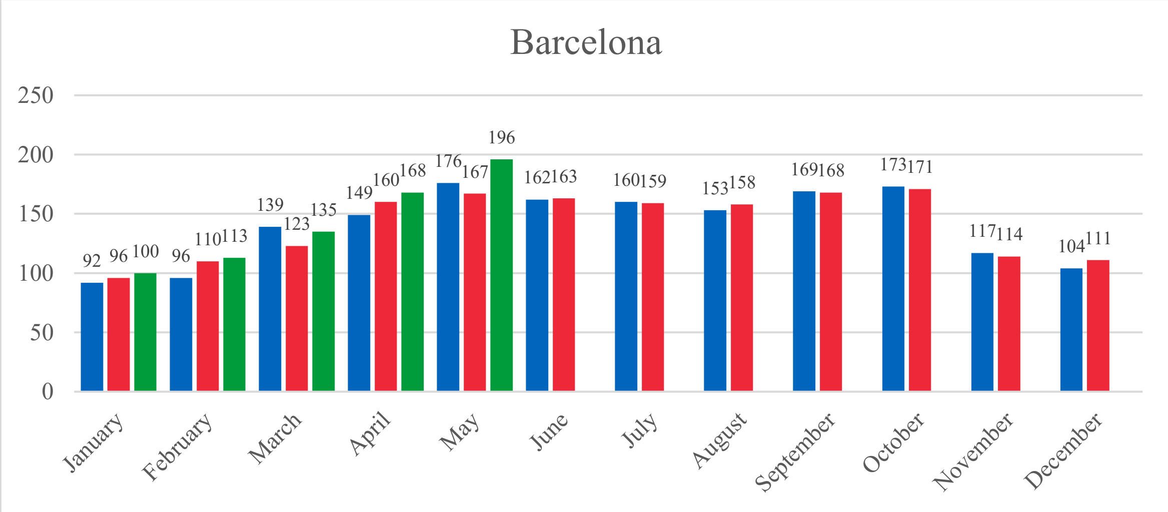
ALL										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	47,90 %	26,33 %	11,89 %	5,45 %	3,17 %	1,97 %	0,92 %	0,61 %	0,47 %	1,27 %
% of 2016	44,34 %	30,67 %	11,16 %	5,12 %	2,72 %	1,79 %	1,03 %	0,81 %	0,49 %	1,82 %
% of 2017	30,27 %	37,95 %	13,53 %	6,23 %	3,55 %	2,14 %	1,69 %	1,03 %	0,79 %	2,77 %
Revenue management of listings with >90 bookings per year										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	38,35 %	30,38 %	14,29 %	6,54 %	3,65 %	2,66 %	1,15 %	0,69 %	0,60 %	1,65 %
% of 2016	38,45 %	34,59 %	12,86 %	5,63 %	2,73 %	1,80 %	1,10 %	0,66 %	0,45 %	1,73 %
% of 2017	19,54 %	40,57 %	15,85 %	7,62 %	4,65 %	2,77 %	2,37 %	1,45 %	1,15 %	4,03 %
Revenue management of listings with >180 bookings per year										
	STD=0	STD<10	STD<20	STD<30	STD<40	STD<50	STD<60	STD<70	STD<80	STD>80
% of 2015	44,87 %	25,63 %	11,05 %	6,15 %	4,21 %	3,19 %	1,37 %	0,46 %	0,46 %	2,62 %
% of 2016	44,02 %	32,53 %	11,89 %	5,10 %	2,15 %	1,63 %	0,86 %	0,51 %	0,15 %	1,16 %
% of 2017	18,93 %	40,55 %	15,17 %	7,49 %	5,02 %	2,87 %	2,71 %	1,60 %	0,97 %	4,70 %

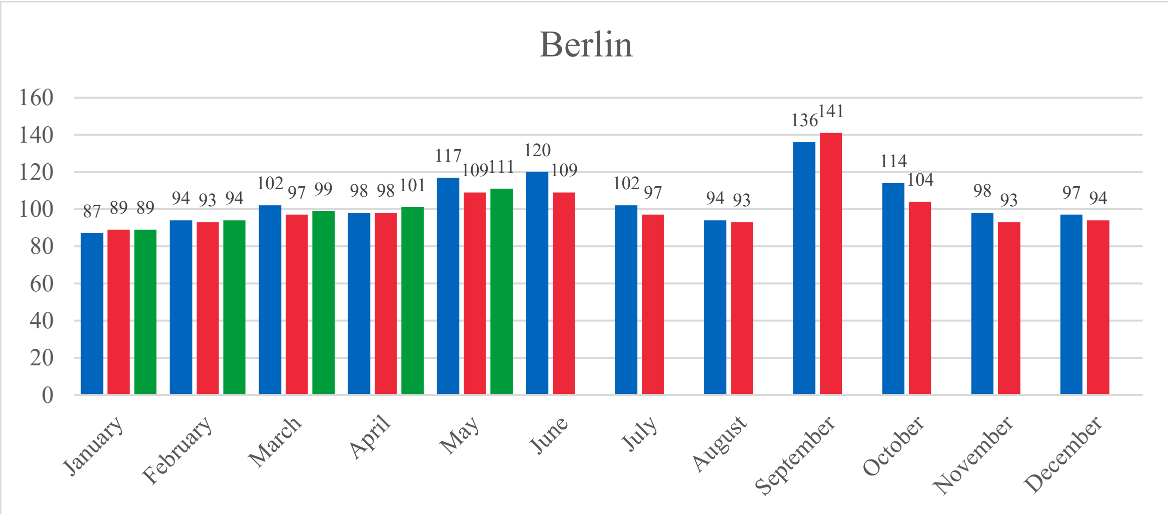
7.2 Appendix B – Trivago hotel price indices

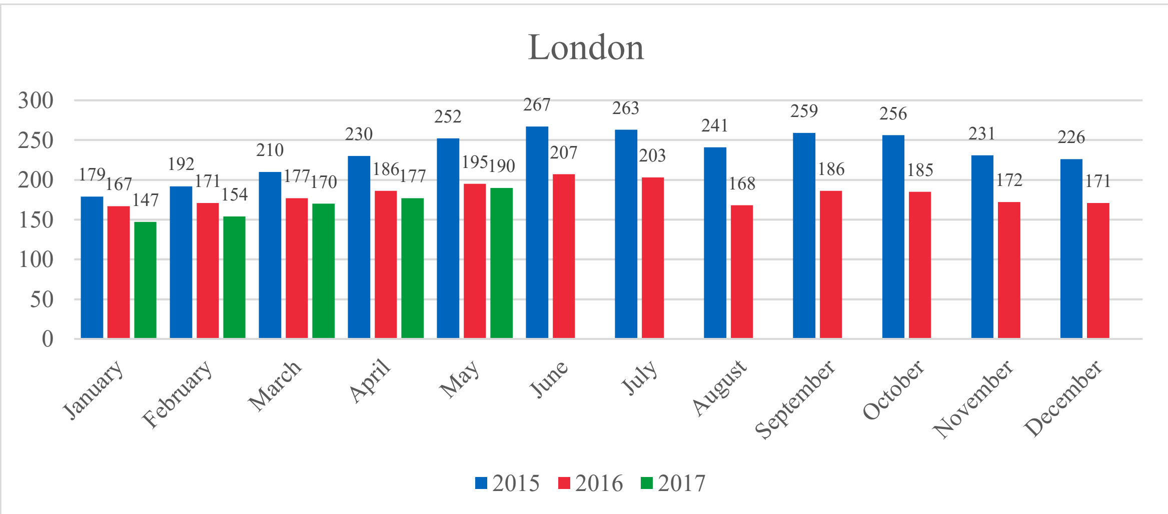


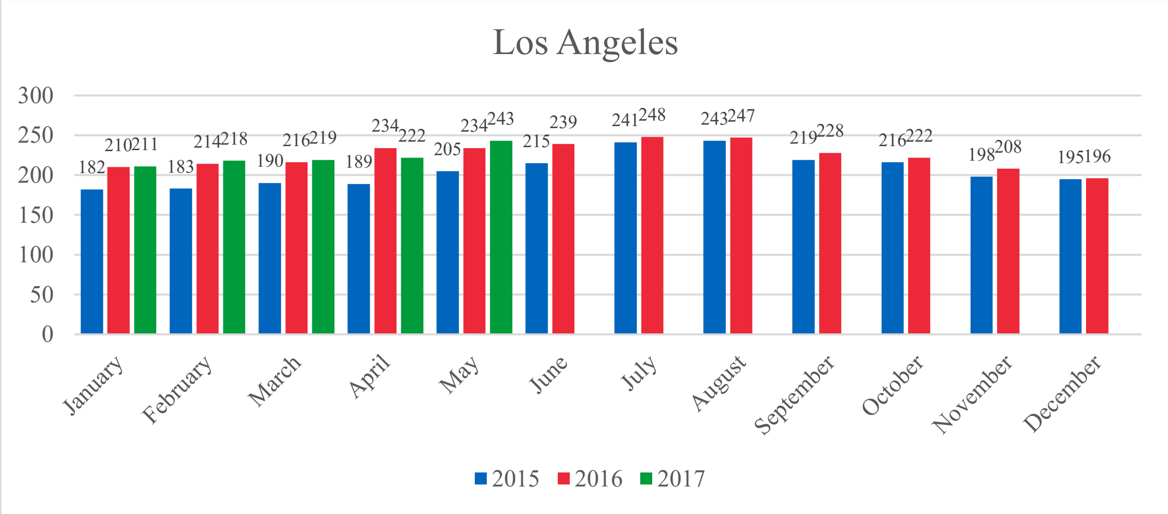





Barcelona
250
200
150
100
50
0
92 96 100 96 110 113 139 123 135 149 160 168 176 167 196 162 163 160 159 153 158 169 168 173 171 117 114 104 111
January
February
March
April
May
June
July
August
September
October
November
December


Berlin
160
140
120
100
80
60
40
20
0
87 89 89 94 93 94 102 97 99 98 98 101 117 109 111 120 109 102 97 94 93 136 141 114 104 98 93 97 94
January
February
March
April
May
June
July
August
September
October
November
December


London
300
250
200
150
100
50
0
179 167 147 192 171 154 210 177 170 230 186 177 252 195 190 267 207 263 203 241 168 259 186 256 185 231 172 226 171
January
February
March
April
May
June
July
August
September
October
November
December
2015 2016 2017


Los Angeles
300
250
200
150
100
50
0
182 210 211
183 214 218
190 216 219
189 234 222
205 234 243
215 239
241 248
243 247
219 228
216 222
198 208
195 196
January
February
March
April
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June
July
August
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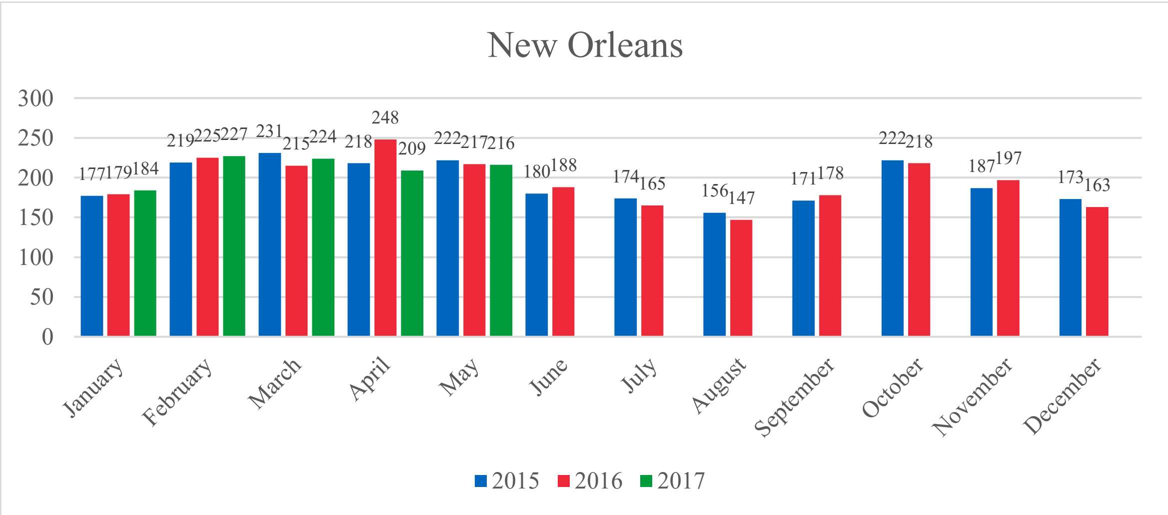
October
November
December
2015 2016 2017


New Orleans
300
250
200
150
100
50
0
177 179 184
219 225 227
231 215 224
218 248 209
222 217 216
180 188
174 165
156 147
171 178
222 218
187 197
173 163
January
February
March
April
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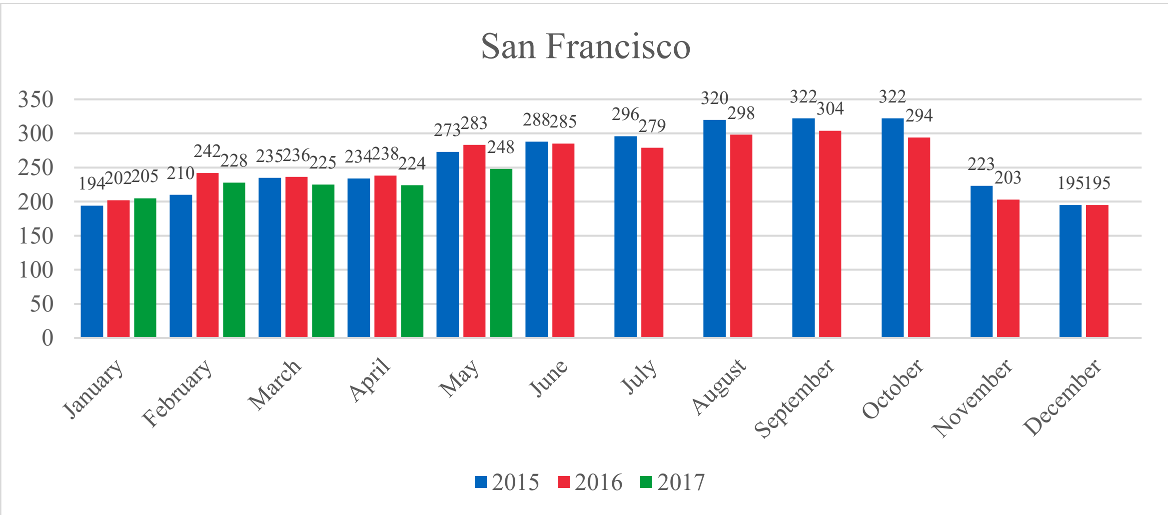
September
October
November
December
2015 2016 2017


San Francisco
350
300
250
200
150
100
50
0
194 202 205
210 242 228
235 236 225
234 238 224
273 283 248
288 285
296 279
320 298
322 304
322 294
223 203
195 195
January
February
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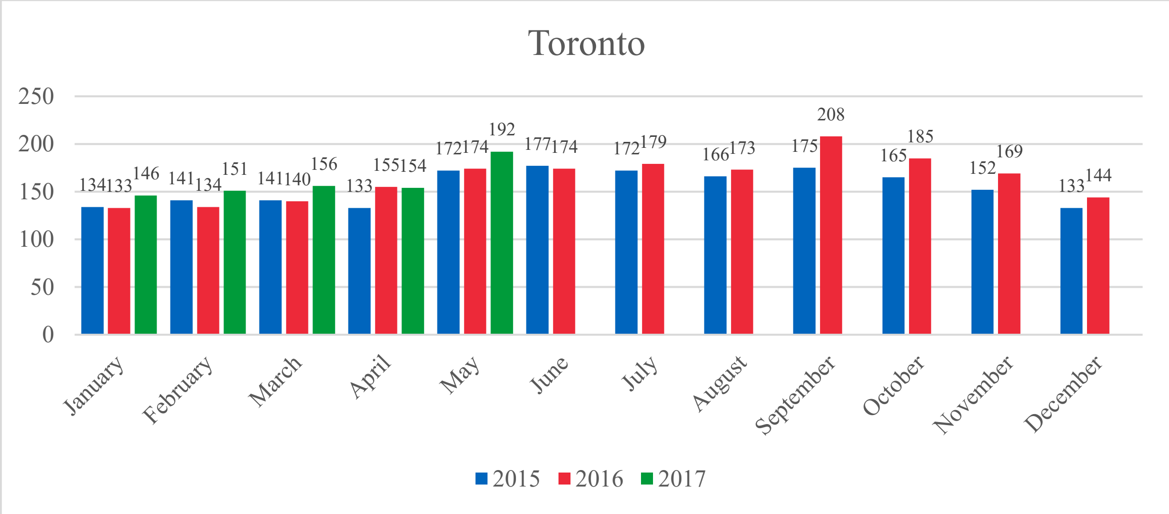
December
2015 2016 2017


Toronto
250
200
150
100
50
0
134 133 146
141 134 151
141 140 156
133 155 154
172 174 192
177 174
172 179
166 173
175 208
165 185
152 169
133 144
January
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July
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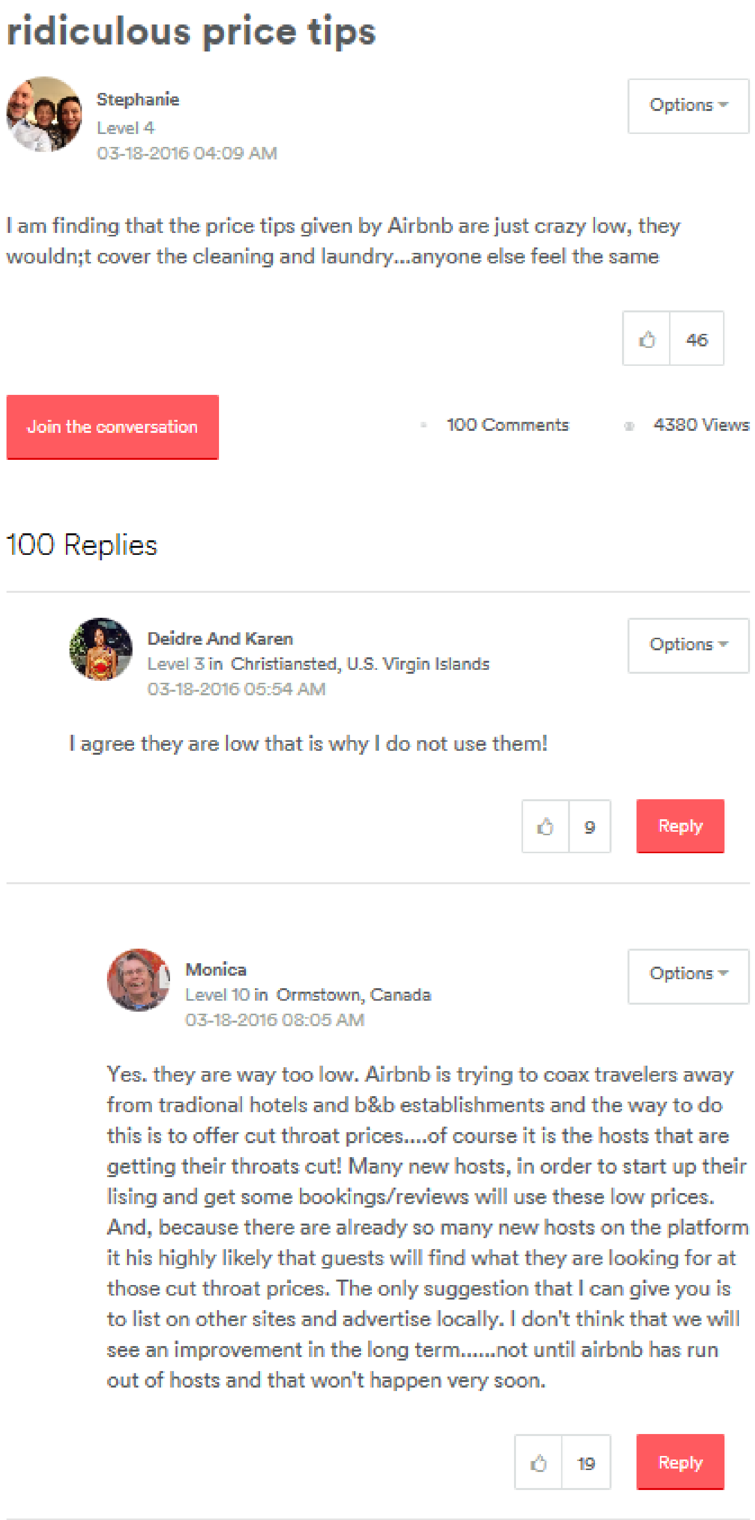
December
2015
2016
2017

7.3 Appendix C – Other

Picture C1: Host comments about Airbnb's poor pricing transparency and price suggestions Airbnb Community Center. (2016-2017). Ridiculous price tips.
https://community.withairbnb.com/t5/Hosting/ridiculous-price-tips/td-p/48793



ridiculous price tips

Stephanie
Level 4
03-18-2016 04:09 AM

Options

I am finding that the price tips given by Airbnb are just crazy low, they wouldn;t cover the cleaning and laundry...anyone else feel the same

46

Join the conversation

100 Comments 4380 Views

100 Replies

Deidre And Karen
Level 3 in Christiansted, U.S. Virgin Islands
03-18-2016 05:54 AM

Options

I agree they are low that is why I do not use them!

9 Reply

Monica
Level 10 in Ormstown, Canada
03-18-2016 08:05 AM

Options

Yes. they are way too low. Airbnb is trying to coax travelers away from tradional hotels and b&b establishments and the way to do this is to offer cut throat prices....of course it is the hosts that are getting their throats cut! Many new hosts, in order to start up their lising and get some bookings/reviews will use these low prices. And, because there are already so many new hosts on the platform it his highly likely that guests will find what they are looking for at those cut throat prices. The only suggestion that I can give you is to list on other sites and advertise locally. I don't think that we will see an improvement in the long term......not until airbnb has run out of hosts and that won't happen very soon.

19 Reply