Louvain School of Management

Airbnb impact on the hotel market in Brussels

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1 | Introduction

1.1 Introduction to the topic

Created in 2007 and already valued at $31 billion in 2019, the platform is a model of profitability. This explosive rise has often been pointed out as being to the detriment of the classic hotel market. Airbnb has been able to develop a profitable and competitive business model, cutting the grass from under the feet of many classic hotels. According to STR [2019], Airbnb is the second largest short-term accommodation supplier with around one million listings available, and just behind Mariott International and his 1.1 million rooms worldwide. The site offers a wide range of accommodations, most of which is fully equipped, can be rented for a short period of time. According to "L'Echo", there exists one Airbnb accommodation for 6 hotel rooms in Brussels in 2017[1]. But is there any impact from Airbnb presence and diversity on hotel industry since Airbnb introduction in Belgium?

This study focuses on Airbnb impact on hotel industry, more particularly on average hotel financial variables in Brussels but also on Airbnb supply diversity on hotel industry competitiveness. Some research have identified Airbnb accommodations and hotel rooms as substitute while others plaid for Airbnb and hotel industry to be complementary.

1.2 Introduction of the research problem

A new competitor on the market could have a negative impact on companies already established on the market. If this competitor is a disruptive innovation, it can train to a substitution effect between incumbents' products and new competitor's products. [Guttentag and Smith, 2017] At the launch of the website company, the disruptive product was underperformed compared to existing products (hotel rooms) and Airbnb improved their disruptive product in order to attract mainstream customers of hotels. Bashir and Verma [2016] have linked disruptive innovation to value creation. Innovation in Airbnb business model by creating "peer-to-peer sharing accommodations" can be a source of value creation by allowing Airbnb to obtain a competitive advantage. Airbnb can create value but must appropriate the value created. For that, Airbnb charges a fee for every transaction for guests (6-12%) and for the host (3% of revenues). Research has shown evidence about a trade-off between value creation and value appropriation despite their interrelationship. [Mizik and Jacobson, 2003] [Pitelis, 2009] Authors want evaluating impact from Airbnb supply on hotel financial variable by differentiating this supply by the type of room[2] in the aim to identify if a certain room type is more comparable to what a hotel proposes. If a certain room type is more considered as a substitute, it means Airbnb is a disruptive innovation attracting hotel industry mainstream customers. Authors also consider other diversity characteristics as amenities or security deposit for instance. **What's Airbnb impact on hotel industry in Brussels by considering diversity supply?**

[1] `https://www.lecho.be/entreprises/horeca/les-chiffres-derriere-le-phenomene-airbnb/9920215.html`

[2] There exist 3 room types in Airbnb accommodations, but authors take into account only two types: entire home/apartment and private room because of the small representativity of shared rooms in the sample (0,86%).

Every city is different. Culture, consumer habits, socio-economic and demographic characteristics, heritage, etc., makes a city unique to visit. As the short-term accommodation sector in each city is different, it can be interesting to know its state in Brussels. Other studies have looked at the impact of airbnb on the hotel market in other major cities but our tourist and business market is not the same as in other countries that have been addressed by these other studies. In Brussels, from a general point of view, there are 6 million overnight stays by non-residents in 2017 [3]. La Libre Belgique revealed in 2017 that the turnover of Airbnb accommodations in Brussels amounted to 34 million euros per year[4]. As the number of accomodations has doubled since then, it can be assumed that this turnover will also double.

Considerable income is generated on the territory of Brussels. But who benefits from this creation of value by Airbnb? Is this value creation to the detriment of that of the hotels? The figures for Airbnb's real market share in Brussels are still unknown, but according to L'Echo, there is one Airbnb accommodation for every 6 hotel rooms in the capital, which is not negligible. Competition is therefore possible. But to what degree? Airbnb is part of this collaborative economy trend, which is relatively new and is in the process of changing our consumption habits. The interest of this work is to quantify the impact of this new means of housing for a very short period of time, and what it implies for the reference in the field, namely the hotel sector.

There is no consensus about considering Airbnb as a concurrent for hotel industry. Authors identify Airbnb accommodations as substitute for hotels if they consider the supply of Airbnb without differentiation with respect to its diversity. By differentiating Airbnb supply by the room type of accommodation, authors advance private rooms are more likely to be a substitute with hotel rooms, through a significant and negative impact on hotel average RevPar (Revenue per Available Room) in Brussels. Security deposit has already been analysed by research as a barrier in accommodation choice. The authors identify security deposit amount also as a barrier in accommodation choice but it concerns mostly entire homes and apartments. When a security deposit amount for an Airbnb accommodation increases, guests are more likely to look towards other Airbnb accommodations and authors identify a possibility certain guests opt for hotel rooms instead of Airbnb accommodations.

First section describes all findings from research on possible competition between hotels and Airbnb and the hypotheses constructed by the authors in regard to research findings. The Method explains the data but also the equations and the model used to estimate the impact of Airbnb on hotel average RevPar in Brussels. In the section Results, results from a regression are analysed through the hypotheses and in the last section, the authors discuss about these results, share the findings in relation to what has already been done by economists but also the limits of this study.

[3] http://ibsa.brussels/chiffres/chiffres-cles-de-la-region#.XsfhqmgzaUk

[4] https://www.lalibre.be/economie/entreprises-startup/airbnb-genere-77-millions-d-euros-dans-6-grandes-villes-belges-59840108cd70d65d252c1e20

2 | Theory and hypothesis

2.1 Litterature review

Resource based-view analysis

According to the Journal of Management, the concept of value creation and the resource-based view of a firm are linked towards the emergence of profits for the firm [Becerra, 2008]. The resource-based view of the firm defines a firm as a bundle of resources and capabilities, which allow the firm creating value [Miller, 2019]. The resource-based view of the firm is a theory developed by Barney in a study which examines the link between firm resources and sustained competitive advantage [Taher, 2012]. Firm resources are defined as *"all assets, capabilities, organizational processes, firm attributes, information, knowledge, etc controlled by a firm that enable the firm to conceive of and implement strategies that improve its efficiency and effectiveness"* [Barney, 1991]. A competitive advantage can be sustained for a firm if this competitive advantage fills in four conditions: value, rareness, inimitability and organization [Barney, 1995]. The notion of competitive advantage is set for a firm when this firm has launched a strategy creating value.

According to Jay B.Barney, the resource-based view is articulated around the idea a firm looks inside its internal resources to release a sustainable competitive advantage. Research has also found some evidence in the sources of sustained competitive advantage through analysing the environment, looking for opportunities and threats [Porter, 2008] or through analysing the fit between firm internal resources and the environment, forming the "Strengths-Weaknesses-Opportunities-Threats" analysis [Nurlansa and Jati, 2017].

In the Harvard Business Review, M.Porter establishes a link between five competitive forces to analyse a sector as the threat of new incomers, the bargaining power of suppliers, the substitution products, concurrence within the industry and the bargaining power of customers to constitute the "Five forces model" [Porter, 2008]. This model has two assumptions which need to be taken into account: homogeneity and perfectly mobile firm resources. According to resource-based view, Barney has adopted two contradictory assumptions with strategic resource heterogeneity and that the resources may be not perfectly mobile across firms in analysing sources of competitive advantage [Barney, 1991].

Interdependence and trade-off between value creation and value capture.

Pitelis [2009] mentions through his study the determinants of firm-level value creation as firm-level infrastructure and strategy, resources and the service they provide, technology and innovativeness and increasing returns to scale. The four determinants [5] are linked between them and allow firms to reduce costs and create value. It also helps a firm to capture value. In a study conducted by Lepak et al. [2007], the authors bring to light three levels of value creation sources (firm level, organisation and society level). Piletis (2016) established a link between value creation and value capture or value appropriation through the fact a firm can capture less, equal or more than the value created by the firm. The term "value" means all value created in a market (competitors, stakeholders) and the concept "value capture/appropriation" concerns the percentage of created value by the firm it can capture but also created value by the mar-

[5] The four determinants of value creation engender "firm differentiation".

ket or competitors it can capture [Lepak et al., 2007]. Pitelis [2009] identifies a correspondence between the concepts of firm differentiation and value capture in the sense that more the firm is differentiated with the competition, more the firm can capture value. In total there are four types of value capture strategies which interact between them and linked with value creation. This study establishes an evolutive link between value creation and value capture but also a trade-off between these two economic theories. Research has shown evidence about a trade-off between value creation and value appropriation because of firm capabilities allocation between customer-value creation capabilities and value appropriation capabilities despite their interrelationship [Mizik and Jacobson, 2003] [Pitelis, 2009]. Becerra [2008] has also explored the trade-off relationship between these two economic concepts with the intent to prove that organisational processes inside a firm can train a sustained advantage.

The principal way used by Airbnb to capture value is to charges a fee for each transaction: as a traveller, you will pay a 6-12% Airbnb service fee in addition to the price set by the host (the higher the booking price, the lower the service fee). As a host, you will leave 3% of your annual revenue to the site.

One other way used by Airbnb to capture value is the use of a security deposit when renting an Airbnb. It consists of a sum paid by the guest to Airbnb before the beginning of his stay. It will only be returned to him at the end, less any damage he may have caused in the accommodation. For Airbnb, this gives it a significant competitive advantage in terms of value capture compared to similar platforms. They can use this money to pay salaries, expand their networks and develop their business. It's a kind of short-term loan from the guest to Airbnb. [Reinhold and Dolnicar, 2018]

Airbnb as a disruptive innovation and substitution effect

Bashir and Verma [2016] have linked disruptive innovation to value creation. Innovation in business models can be a source of value creation. Airbnb has broken the codes in the hotel industry by bringing in a new source of supply that competitors have never considered. Innovation in business models can be a source of sustainable competitive advantage that competitors would find it very difficult to emulate. As a result of the significant investments made, they have developed a new way to create and capture value.

Value proposition and value creation processes are described by Reinhold and Dolnicar [2018]. Airbnb's value proposition is for the benefit of its stakeholders. Guests and hosts are connected in a secure, coordinated manner that meets their respective needs and expectations. Value creation for Airbnb is achieved through key activities and key resources. Key activities are the routine behaviours that enable Airbnb to fulfil the value proposition. Key resources enable Airbnb to deliver the value proposition through its key activities and business processes. Ideally, these resources are provider specific and cannot be easily substituted or imitated by competitors. While they are also scarce and valuable, they are potentially used to establish competitive advantage.

As regards value capture, according to Bashir and Verma [2016], Airbnb has developed a commission-based value capture model. They allow the owner to control the price, but systematically take a percentage of it. Airbnb has almost no costs for rental properties since the owner is responsible for the entire amount. Moreover, again according to Bashir and Verma [2016], the company, unlike other hotel groups, does not spend much money on building large infrastructure such as hotels and properties, which gives it a competitive advantage over its competitors.

Li and Srinivasan [2019] defined consumer heterogeneity as a competitive advantage of Airbnb over hotels. Indeed, because of the greater diversity of its offer, Airbnb is able to respond more specifically to the needs of each customer by offering accommodation that corresponds to his or her needs. Airbnb offers a much wider range of products and services than hotels: Airbnb users can rent anything they want, from apartments to yurts [Zervas et al., 2017].

In a study seek by Guttentag and Smith [2017] on a panel of Airbnb users, two thirds of them report using this type of accommodation as a substitute for a hotel and only 2.3% report using an Airbnb for a trip they would not have taken otherwise. According to Neeser [2015], there is no negative relationship between Airbnb and the hotels' RevPar, but Airbnb does contribute to lower prices in the markets where it enters most. Strømmen-Bakhtiar and Vinogradov [2019] who studied the impact of Airbnb on the hotel market in Norway point out that they have not detected a negative relationship between the presence of Airbnb and the profitability of hotels but they even found an independent positive effect between the presence of Airbnb and the number of rooms and nights sold by the hotels. They have based their analysis on a comparison between regions where Airbnb has a strong presence in relation to hotels and regions where it is much less.

However, Blal et al. [2018] report that growth in Airbnb's supply is negatively associated with hotel performance. They also argue that when a consumer chooses accommodation, they will consider both products, hotels and Airbnb, in the decision, comparing the advantages and disadvantages of each through reviews, price, and amenities. This behaviour is an indicator of a substitution situation.

Disruptive innovation as a value creation

Research has made some evidence between Airbnb and disruptive innovation, a concept created by Christensen in the 1990s. According to Christensen [2013], a disruptive product procures a new value proposition. In the "Harvard Business Review", Christensen and al. describe this concept as a process designed by a small entrant firm with small resources in order to disrupt an existing market [Christensen et al., 2015]. The incumbents in this market are concentrating on improving products meeting needs from mainstream customers who represent the segment with higher profitability for incumbents. New entrant targets the overlooked segments by generally cheaper products or in a more convenient way through a new value network on the market and try to move up the market by offering solutions that appeal to mainstream customers of incumbents. As the disruptive product looks like existing products in terms of attributes, these products are substitute [Guttentag and Smith, 2017]. The consequences of a disrupt product provokes the low-end of the market or causes a new market [Guttentag, 2015]. J.Paap and R.Katz for the Research-Technoly Management have identified some elements that could anticipate a disruptive innovation for the incumbents [Paap and Katz, 2004].

A study conducted by Guttentag [2015] has examined the application of the disruptive innovation theory framework to Airbnb compared with hotel industry, a website company in the accommodation tourism sector. Airbnb has provided a new internet-based business model by creating the "peer-to-peer accommodation". At the launch of the website company, the disruptive product was underperformed compared to existing products (hotel rooms) and Airbnb improved their disruptive product in order to attract mainstream customers of hotels, as the disruptive innovation testifies. Another pattern of disruptive innovation theory is completed by Airbnb's growth, the limit of success as a disruptive product and a size increase as the disruptive product enters the mainstream market. According to a study conducted by Guttentag [2016], the "peer-to-peer accommodation", implemented by Airbnb is a disruptive innovation. The author have discovered a substitution effect between hotels and Airbnb. A study conducted by Bashir and Verma [2016] has identified the business model of Airbnb as a disruptive innovation. They argued that Airbnb has an unique value proposition through business model innovation in order to create value.

According to Zervas et al. [2017], the decline in hotel revenues in some areas due to Airbnb's presence is as much as 8 to 10%. This study was carried out in Texas in several cities of the state, it shows that an increase in the Airbnb supply by 10% is accompanied by a decrease in monthly room revenue of 0.39%. Taking the city of Austin as an example, where penetration was the highest with an increase in the number of Airbnb from 450 in 2010 to 8500 in 2014, they arrive at a decrease in revenue of around 10%. According to Gallic and Malardé [2018], low- and mid-range hotels would be more affected by the presence of Airbnb than high-end hotels.

Airbnb's growth is fairly heterogeneous over time. Farronato and Fradkin [2018] studied Airbnb's market shares in several major American cities. During the year 2014, out of the 50 largest cities in the United States, Airbnb's market share is between 1 and 15%. The gain if Airbnb had not been present has also been estimated and is also quite heterogeneous. For example, in New York, bookings would increase by 2% and revenues would increase by 2.24% without Airbnb. In contrast, in San Jose, a city where hotels are less likely to meet their capacity constraints, reservations would increase by 0.63% and revenues by 0.72%.

Although these figures are impressive, Farronato and Fradkin [2018] put Airbnb's real impact into perspective. They point out that the elasticity of supply of Airbnb is higher than that of hotels, but the presence of Airbnb has only a small effect on hotel revenues. However (Neeser, 2015) states that Airbnb had a negative impact on average daily hotel rates but had no impact on disposable income per room, suggesting that hotels reduce rates in order to maintain occupancy levels. A study conducted by Xie and Kwok [2017] showed a significant link between the difference in the price gap between Airbnb and hotels and the performance of these same hotels. They confirmed, on the one hand, that Airbnb's offer has a negative impact on the hotels' RevPar, but, on the other hand, that the hotels' RevPar increases with the increase in the price difference between the hotels and Airbnb. They explain this by a greater price difference between Airbnb's advertisements and the hotels indicates that the price positioning of these two competitors is increasingly divergent, so they meet a different clientele.

Amenities and context studies

Those who choose Airbnb are primarily motivated for economic reasons. Dogru and Pekin [2017] have shown that Airbnb customers place more importance on space, cleanliness, number of photos, accessibility for disabled people, family friendliness, free breakfast, location and unique experiences. Airbnb guests also appreciate and pay more for more photos of the Airbnb properties; however, they pay lower rates for Airbnb properties that seem to have commercial purposes.

According to a study by Cheng and Jin [2019] based on a panel of Airbnb guests, the voters declare that they are important when choosing a rental: to the place (100%), to the amenities of the accommodation (81%), to the host (70%) and finally to the recommendations (18%). Guttentag [2016] also points out that the main factor in choosing an Airbnb is above all the price, which is cheaper than the hotel market. He noted that the factors most highly correlated with what a guest would pay were sleeping capacity, whether the rental is for an entire home or a private room, the type of property (e.g., apartment or house), and the quantity of reviews. Using the hedonic price method to determine the importance of amenities in the price of an Airbnb, Dogru and Pekin [2017] into further detail by showing that Airbnb customers place more importance on space, cleanliness, number of photos, accessibility for disabled people, family friendliness, free breakfast, location and unique experiences. They also show that the presence of a kitchen and the authorisation of animals lower the price of the rental, unlike wheelchair access or family-friendly accommodation that makes it go up. Wang and Nicolau [2017] add that the nature of the host, site and property attributes, amenities and services, rental rules and online evaluations all influence the price and availability of the property.

2.2 Hypothesis

A new competitor on the market could have a negative impact on companies already established on the market and if innovation constructed by the new competitor is disruptive, there will be a substitution effect in a second time[6] [Guttentag and Smith, 2017]. According to them, nearly two thirds of Airbnb users report using this type of accommodation as a substitute for a hotel. However, according to Neeser [2015], there is no negative relationship between Airbnb and the hotels' RevPar, but Airbnb does contribute to lower prices in the markets where it enters most. Strømmen-Bakhtiar and Vinogradov [2019] and Mhlanga [2019] have found in their respective studies there is no relationship between the Airbnb supply and profitability of the hotels and the price. The second even add that the hotel occupancy is negatively impacted.

Strømmen-Bakhtiar and Vinogradov [2019] even found an independent positive effect between the presence of Airbnb and the number of rooms and nights sold by the hotels. It is plausible that Airbnb customers who would not otherwise visit the region could spend a few nights in a hotel, which would lead to an increase in demand in this sector as well. It is also possible that greater Airbnb penetration would help to disseminate information about the destination and signal to potential tourists that a particular region is a well-developed tourist destination.

However, in a study conducted in Texas by Zervas et al. [2017], in the Austin market, where Airbnb's supply is the largest and penetration is the highest, hotel revenues are negatively affected. Authors test Airbnb presence on hotel average RevPar to identify substitution effect between Airbnb accommodations and hotel rooms through a negative impact. By impacting negatively hotel average RevPar, Airbnb would be considered as a disruptive innovation for the hotel industry.

Hypothesis 1 *Airbnb supply has a negative impact on the hotel average RevPar.*

Not all players in the hotel market will be affected in the same way. Zervas et al. [2017] have shown that some hotel segments are more affected than others by the presence of Airbnb. Guttentag [2015] described that the threat of Airbnb's entry and growth is directly felt by low-end hotels because the prices of private rooms are generally equivalent to those of rooms in low-end hotels, i.e. 1 to 2 stars. The study by Zervas et al. [2017] also showed that Airbnb's penetration was negatively associated with hotel revenue.

Hypothesis 1A *The negative impact from Airbnb supply on hotel average RevPar decrease as hotel category increases.*

Through a hedonic model pricing Young et al. [2017] identifies type of room as determinants among others of Airbnb accommodation prices. Guttentag and Smith [2017] considers a substitution effect between Airbnb and hotel rooms through a disruptive innovation. The authors advance type of room can be a factor of this substitution effect. Airbnb accommodations distinct themselves by two distinctions: 'room type' (entire home/apartment, private room and shared room) and 'property type' (castle, farm, house, boats,..). The authors only considered the room type in this study because of the limited number of different room types, which makes the benefit analysis controlled. Indeed, there are dozens of possible property types, the authors assumed that an analysis made on this basis would have been much too evasive and would not have given significant results. According to figures from insideairbnb, in Brussels, there are significantly more entire home/apartment in regions covered by this study, around 64.5%.

[6] In a first time, a disruptive innovation proposes other solutions for customers which are not considered as the mainstream customers for hotel industry, in the case of this study.

In an entire house, all place is private and it usually includes living rooms such as bathroom, bedroom,... According airbnb.com, a private room concerns a room for sleeping and other areas need to be shared. Shared room are shared bedrooms with hosts and/or guests in the same room.

Authors constructed two interaction terms between a continuous variable, the "PenetrationRate" and a dummy variable "PrivateRoom" and the "PenetrationRate" and a dummy variable "dEntireHome" to assess the impact from a certain type of room on the hotel average RevPAR in Brussels. The variable PenetrationRate is described in Measures page 16. Guttentag [2015] has identified entire home/apartment and private room type as substitute of hotel rooms. From author's point of view, a private room is the most substitutable product proposed by Airbnb accommodations in regard to classic hotel rooms compared with the entire home/apartment. In fact, the private offer corresponds more to what is offered in a hotel, i.e. a single room for one or two people. On the other hand, the entire home is aimed more at small groups looking for more autonomy, which does not correspond to the hotel offer. Airbnb value capture increase when it is a private room by impacting negatively the average hotel RevPar.

Hypothesis 1B *The joined effect from Penetration Rate and the private room type has a negative impact on average hotel RevPar.*

Hypothesis 1C *The joined effect from Penetration Rate and the entire home/apartment type has a positive impact on average hotel RevPar.*

The substitution effect between Airbnb and hotel rooms can be proven by another way than testing Airbnb supply on hotel RevPar by testing substitution effect theory. According to Investopedia[7], *"substitution effect is the decrease in sales for a product that can be attributed to consumers switching to cheaper alternatives when its price rises."* The sales in accommodation market concerns the number of booked nights. The hotel occupancy rate can be seen as a proxy of the number of booked nights. By testing Airbnb average price on hotel occupancy rate, authors could confirm or infirm substitution effect between Airbnb supply and hotel RevPar.

Some research assesses Airbnb impact on hotel RevPar through mainly the Airbnb supply effect, but none assesses Airbnb impact on hotel RevPar through Airbnb occupancy rate. This occupancy rate is constructed as the method build by Department [2015] explained in the section Measures. If substitution effect is considered as found by Guttentag and Smith [2017] through Airbnb supply effect, Airbnb occupancy rate impacts negatively the hotel average RevPar. By impacting negatively hotel RevPar, Airbnb accommodations increase their value capture by impacting value hotel appropriation.

Hypothesis 2 *Airbnb price has a positive impact on hotels average occupancy rate.*

Hypothesis 3 *Airbnb monthly occupancy rate has a negative impact on the hotel average RevPar.*

In the context of an Airbnb, the RevPar is defined by the airdna.co website as the Revenue Per Available Rental. It is calculated with Average Daily Rate and Occupancy Rate. The Average Daily Rate is defined as the daily price at which a reservation is booked. The Occupancy Rate is the occupancy rate of accommodation in relation to the period during which it is available for rental. An interaction term between Airbnb price and Airbnb occupancy rate allows authors to construct the Airbnb RevPar. Authors wish to experiment with the theoretical parallel between the RevPAR of hotels in a certain area and the calculated RevPar of Airbnb. By considering substitution effect between Airbnb and hotels, Airbnb RevPar should impact negatively average hotel RevPar increasing Airbnb accommodations value capture through diminishing hotels value appropriation in Brussels.

[7] `https://www.investopedia.com/terms/s/substitution-effect.asp`

Hypothesis 4 *The combined effect from Airbnb price and Airbnb occupancy rate impact negatively hotel average RevPar.*

The amount of a security deposit, sometimes several hundred dollars, can be a barrier for renters. Benjamin et al. [1998] claims that rental rates for a property decrease when the amount of the deposit increases. An Airbnb accommodation with a security deposit would therefore be less suitable for renting than one that is not subject to, or a hotel for which there is no security deposit. The authors assume a value capture on the part of the hotels to the detriment of the bonded Airbnb. Qiu et al. [2018] report that extra charges, such as security deposit, cleaning fees, and the fees for extra people, would keep guests from booking.

Unlike Airbnb, hotels do not require a deposit, the traveller only pays room price. Consumers who are not able to pay the security deposit amount for an Airbnb rental are led to turn to a cheaper option. [Benjamin et al., 1998] To the extent that a person gives up Airbnb accommodation subject to a deposit and opts for a solution that does not require spending a large amount of money before even enjoying the accommodation, potentially a hotel, the amount of a security deposit for Airbnb accommodation would have a positive impact on average hotel revenue per available room.

Hypothesis 5 *The amount of a security deposit for Airbnb accommodation has a positive impact on hotel average RevPar.*

In hotel industry, there exists standards for each hotel category level. Some Airbnb accommodations stand out from these standards with other services or presence of amenities. In Airbnb data, we obtained a list of amenities, representing by a bunch of binary variables. Airbnb supply is characterised by several parameters describing the accommodation known as amenities which are services or present goods within the accommodation such as the presence of a gymnastics room [Li and Srinivasan, 2019]. Amenities consist mainly in basic amenities present in each hotel and accommodation as towels but there are some amenities such as gymnastics, which allow Airbnb accommodation to differentiate from other accommodation offers.

As Bascle [2016] mentioned in his study, *"an intermediate conformer is an actor who is neither totally conformed or non-conformed to social norms"*. An actor can be an individual or an organisation, such as Airbnb. This theory can be applied to our study by seeing Airbnb as an intermediate conformer even if it's applicable to social norms. Indeed, an Airbnb accommodation is an intermediate conformer if it doesn't fill in same standards as hotel industry depending on hotel category level, which correspond to social norms in the framework developed by Bascle [2016] and if it fills in some norms which aren't considered in the hotel industry such as the possibility of smoking inside. This framework is applied to Airbnb and hotel industry because the authors suppose Airbnb to follow an attainable norm but is not at the highest level of conformity. Under such assumption, Airbnb can manage legitimacy by compensating.

Indeed, for instance, Airbnb can follow another norm as the presence of an outdoor space for the guests and not follow a standard within hotel industry such as the presence of a swimming pool, defining a certain conformity level. This conformity level can generate a compensation effect for the actor if the social approval of the implemented norm (outdoor space) is greater than the loss due to the unattainability of the rejected norm (swimming pool).

If the implementation of an outdoor space outweighs the loss of capturing value because of the absence of swimming pool in terms of value capture by Airbnb, it generates a compensation effect for Airbnb by a supposed impacting negatively hotel financial variables. Value creation coming from Airbnb accommodations impact the hotel value capture/appropriation as a function of Airbnb accommodations position regarding hotel standards.

Through interaction terms applicable to a correlated-random effects model, the authors can test the presence of compensation effect for Airbnb by comparing Airbnb supply through amenities and hotel standards. Airbnb follows other amenities than hotel standards on the grounds of law and inversely.

Hotels are classed by number of stars. This classification is established by the European association "Hotelstars Union" of which Belgium is a member. This new European grid proposes a uniform classification of hotels on the basis of common criteria. The aim is to provide customers with rigorous and reliable information, in complete transparency. It is based on criteria divided into 7 areas: general hotel information, reception and services, furnishings, gastronomy, event facilities, leisure activities and quality and online activities. Each hotel needs to respect these standards to access superior category level. In our data, we dispose about hotel financial variables for 3-,4- and 5-stars hotel. Authors consider this document as a basis for hotel standards. We advance the 3-stars hotel standards to be the European hotel average supply. The standards for each hotel category level are by European Economic Chamber of Trade, Commerce and Industry [2012].

To differentiate amenities that could benefit or harm financial hotel variables, the authors identify the amenities which are considered in the average supply from a hotel in Europe and amenities which aren't considered into. The amenities considered in Airbnb data and chosen by authors are a kitchen, outdoor space, pet friendly accommodations, wheelchair access, free parking, luggage drop-off, the possibility of long-term stays, smoking allowed, a private entrance, a 24hour check-in/-out, a swimming pool and a gymnastics room. The amenities which are considered in 3-stars hotels standards are luggage drop-off, a 24hour check-in/-out and free parking. They form the amenities group which are common between Airbnb accommodations and hotel standards.

In Bascle [2016], the author identifies a link between a company value creation and competitors value appropriation. Indeed, Southwest Airlines by being an intermediate conformer offers services above and below competitor standards and has impacted negatively competitors value appropriation. Through this hypothesis, the authors want to identify Airbnb as an intermediate conformer to prove Airbnb can create value and impact hotels value appropriation negatively.

Hypothesis 6 *Airbnb can benefit from a compensation effect by following another norm than standard norms for hotel industry which can be translated as a negative impact on average hotel RevPar by Airbnb pursuing the achievement of another norm (outdoor space) than standard hotel industry (swimming pool).*

According to Guttentag [2015], more Airbnb accommodations are copying upmarket segments (hotel rooms) through the concept of disruptive innovation, higher is the substitution effect. More Airbnb accommodations have amenities presence considered in hotel average offer (3-stars hotel standards) more hotel rooms and Airbnb accommodations are substitute. On this basis, the presence of an amenity considered in average hotel supply has a negative impact on financial hotel variables. We extent this link to all amenities for the reason that if it's an amenity does not present in average hotel supply, the presence of such an amenity in Airbnb accommodations impacts negatively hotel average RevPar.

Through this hypothesis, authors want identifying the fact Airbnb is a disruptive innovation copying upmarket segment and being substitute to hotel rooms. As hotel category level increases, required hotel standards increase and supply is more and more diversified. The authors advance presence of an amenity considered in 2-stars hotels standards has more negative impact on 2-stars RevPar than on 3-stars RevPar hotels among financial hotel variables.

Hypothesis 7 *The presence of amenities in Airbnb accommodations impact negatively hotel average RevPar.*

Hypothesis 7A *The negative impact from the presence of an amenity in Airbnb accommodations considered in 3-stars standard hotels have less and less negative impact on hotel average RevPar as category hotel level increases.*

2.3 Conceptual model

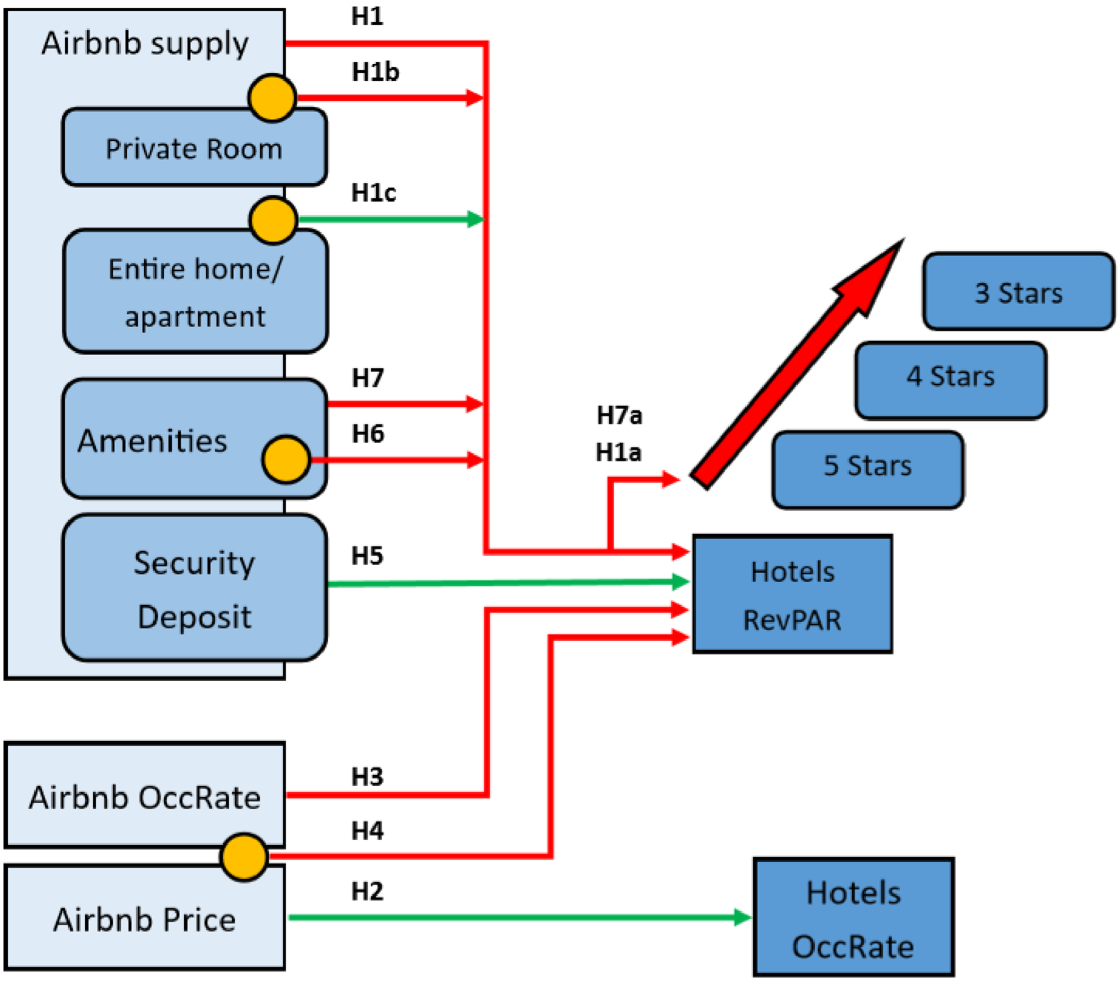
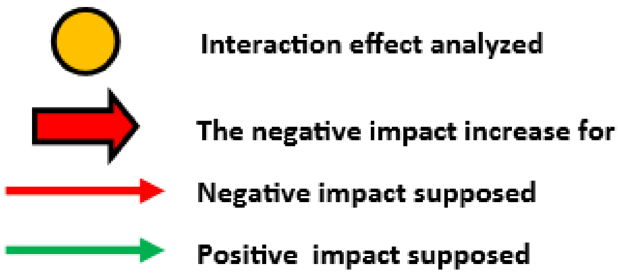


Figure 2.1: Conceptual model



3 | Method

3.1 Data and sample

Hotels

We obtained monthly hotels financial data from MKG Consulting for 66 hotels in Brussels (nearly one third of the supply in Brussels) for the period from January 2010 to December 2019. To maintain data confidentiality, MKG Consulting provided us average financial data for all Brussels territory, average financial data for Brussels areas and average financial data according to the category level, represented by the number of stars a hotel has. They provided us also average financial data only for 3 stars, 4 stars and 5 stars hotels but not for hotels from lower categories because of a lack of representativeness in the sample of low-end hotels. We used these average financial data as dependent variables in our model, we are looking to assess the impact of Airbnb supply and its diversity on the average occupancy rate, the average daily rate and the average revenue per available room of hotels.

Airbnb

The data collected relating to Airbnb comes from insideairbnb.com, a site that collects via a scrapping method the data presented on Airbnb's website. It is possible for us to obtain various information relating to Airbnb in Brussels, the site offers a large panel of major cities whose data is available. What interested us were the listings of the different Airbnb present on the territory of the Brussels Capital Region (not to be confused with the municipality of Brussels, which is only one of the 19 municipalities of the Brussels Capital Region). These listings have been established since 2015, but with different time intervals. Therefore, it is only since May 2018 that a monthly census has been carried out by the site and is available. These listings list all the recent accommodations on the Airbnb site. Many characteristics are also associated with them such as location by geographical coordinates, amenities, prices, availability, reviews and many others.

Control variables

Some data concerning the following control variables: NightMeetingMonth, the number of overnight stays recorded per month in all types of accommodation for business reason, NightLeisureMonth is the same but for leisure reason. These control variables come from Brussels hotel barometer conducted by Visits Brussels, Brussels Tourist Office.

Time and location

The unbalanced[8] panel data considered in this study concerns 20 monthly time periods from May 2018 and December 2019 on Brussels territory, classified into 6 areas: Brussels Airport, Grand Place et environs, Midi-Lemonnier, Quartier Européen, Quartier Louise and Rogier/Botanique as shown in the next sub-section. This segmentation of hotels by area was established about ten years ago when the hotel barometer of the city of Brussels was set up.

3.2 Measures

Geographical segmentation

As described above, the list of hotels provided by MKG Consulting contained 66 hotels, all in the Brussels Capital Region, the area on which we are focusing our study. They are themselves divided into 6 areas. The list of these hotels is invariant over time, only the financial data associated with the different areas and hotel categories are monthly. For each of these hotels, we have determined the geographical position in Brussels. Most hotels included in this listing are located in the centre.

In order to carry out the geographical segmentation, we based on a segmentation carried out by the City of Brussels via its website monitoringdesquartiers.brussels, which proposed a segmentation by districts for the whole city of Brussels. This segmentation has the advantage of being quite detailed so that, even despite the high concentration of hotels in the centre of the City of Brussels, it is possible to distinguish several districts and allow a more precise analysis. Using this geographical segmentation, it was possible to determine which hotel is located in which district. Since each hotel is also associated with an area (according to the MKG Consulting listing) and can be located in a district according to its geographical coordinates, we grouped groups of districts to form the areas from a geographical point of view. Thanks to this, we have an overview of the geographical segmentation of the areas.

Airbnb

Airbnb housing covers the entire Brussels Capital Region. In order to correspond to the areas and to concentrate our statistical study of the districts shared between the hotels and the Airbnb, we have restricted our selection of Airbnb accommodation to the areas concerned.

Each Airbnb accommodation owns an ID, as well as a series of associated characteristics such as price, availability, amenities, location, etc. Our data must be unbalanced panel data for the reason that each Airbnb accommodation is not scrapped by insideairbnb.co each month during our study period implying that Airbnb supply changes over time. The variable Airbnb supply is created for each period and each area. It corresponds to the number of Airbnb accommodations in each area.

Authors have constructed an Airbnb occupancy rate as explained by Department [2015] and on the website insideairbnb.com. The calculation is expressed as followed: the number of reviews per month for each Airbnb multiplied by a review rate gives the number of real estimated bookings. The number of estimated bookings multiplied by the average length of stay (3 nights per booking) and the total is divided by the number of days in a month (30 days) to obtain a monthly Airbnb occupancy rate for each Airbnb. The review rate considered in this study is 50%. Concerning the average length to stay in Airbnb accommodation, it's different for each city but when there is no public statement about it which is the case for Brussels, the average length of stay is equal to 3 nights. The site clearly states in this methodology that this is an

[8] According analytics.brussels, the total number of hotels in Brussels is 190. More details about it in Descriptive variables.

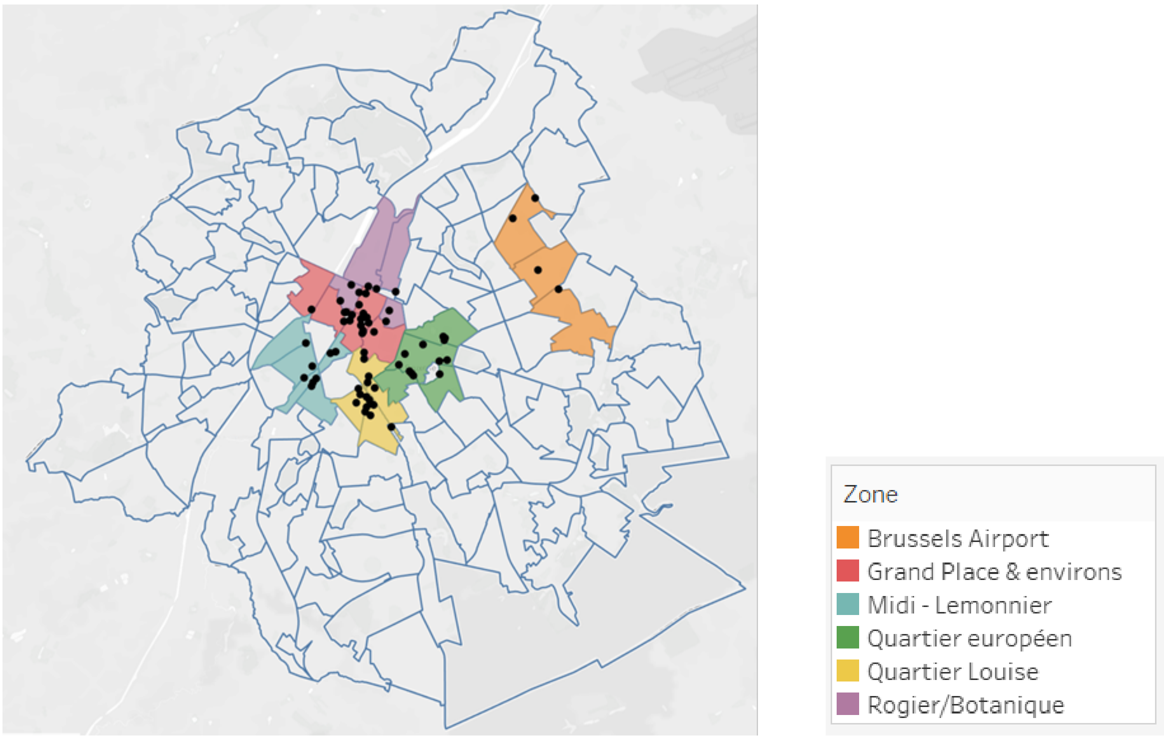


Figure 3.1: *This map shows the different hotels (black dots) included in the MKG listing. The boundaries show us the district segmentation and the different colours represent the different areas considered. Source : MKG Consulting and Monitoring des Quartiers*

approximation of the occupancy rate. Indeed, the length of stay as well as the proportion of users leaving a review can vary. Moreover, a dwelling can only be rented partially. The occupancy rate must therefore be reported at the times when the dwelling is rentable.

The Airbnb penetration rate is defined as the proportion of Airbnb of the same type in a certain area at a certain time. Each dwelling corresponds to a certain type of room (entire home/apartment, private room or shared room), the penetration rate associated with an Airbnb corresponds to the proportion of its type in its zone for the period treated. In order to assess our model, we have constructed our data as unbalanced panel data with a monthly period time and with as observation variables the id Airbnb and for each Airbnb, we have aligned the observed hotel financial variables in the same area.

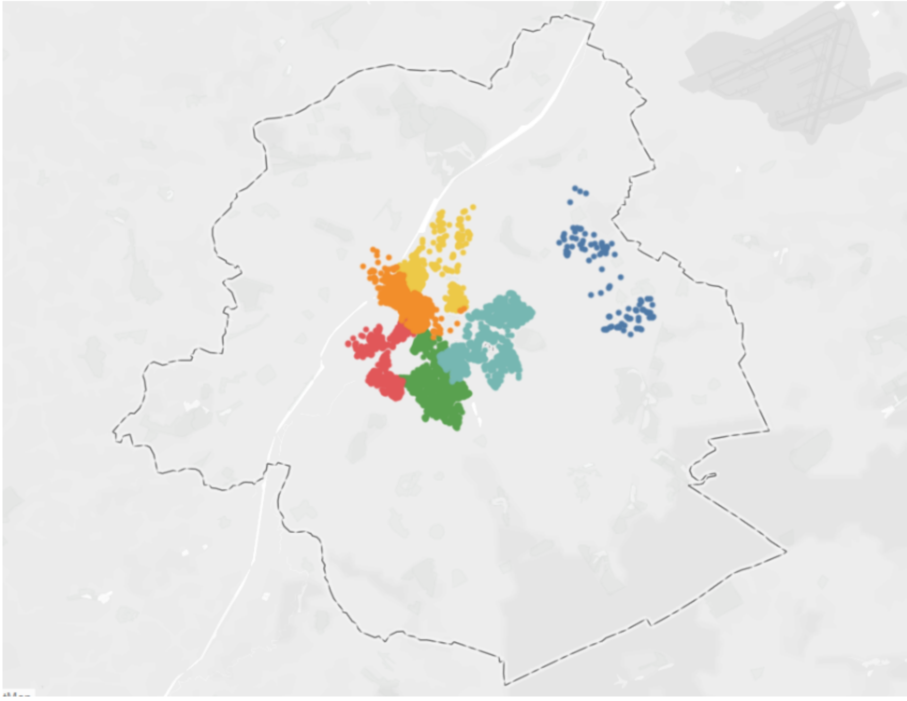


Figure 3.2: *This map of Brussels of the Airbnb present in the areas that also contain hotels. The colours correspond to the different areas. Each Airbnb is compared to the hotel financial performance of the area in which it is located.*
Source : Inside Airbnb

3.3 Analysis

While past studies are concentrating on the impact of Airbnb's supply and Airbnb characteristics on financial performance of the hotel industry, this study focus on how hotel financial variables (ADR, Occupancy rate and RevPar) behave over time and how Airbnb integration affects these hotels in Brussels considering RevPar as the most representative variable of the financial health of hotels. We present in this section our econometric model we have adopted to assess Airbnb's impact on hotel financial variables.

In presence of unbalanced panel data, we have adopted a correlated random-effects approach, proposed by Mundlack in 1978 and improved by Wooldridge. At the first place, we were looking at a fixed-effect model but the major drawback was problematic to demonstrate the hypotheses. Indeed, a fixed-effect model doesn't allow to estimate the effect of variables which don't vary within clusters Schunck [2013], the model deleting these variables effects. It is not a huge problem in panel-data analysis but can constitute a problem if the study focus is to assess the impact of these time invariant variables. In order to bypass this drawback, Mundlack has proposed an approach through a combination of within and between estimates in random-effects model to create the correlated random effects (CRE) framework. This framework allows to estimate random-effects regression models adding group means of variables in independent variables which vary within clusters. This framework relaxes the assumption observed variables are uncorrelated with the unobserved variables in the random-effects estimator Schunck [2013].

In our study, it's very important to control for differences in space and time by creating dummies. Indeed, a geographical area could be confronted to more important hotel prices due to the closeness of a historical centre for instance. Controlling for time differences allows the model not to be impacted by the touristic season. For this reason, we have opted for a CRE approach to assess Airbnb impact on hotel financial variables.

$$
\begin{aligned}
AreaRevPar_{it} = c &+ \beta_1 AirbnbSupply_{it} + \beta_2 + \beta_3 Price_{it} + \beta_4 SecurityDeposit_{it} \\
&+ \beta_5 OccRateAirbnb_{it} + \beta_6 ReviewScores_{it} + \beta_7 Amenities_{it} \\
&+ \beta_8 ControlVariables_{it} + \epsilon_{it} \qquad (3.1) \\
AreaAvPrice_{it} = c &+ \beta_1 AirbnbSupply_{it} + \beta_2 + \beta_3 Price_{it} + \beta_4 SecurityDeposit_{it} \\
&+ \beta_5 OccRateAirbnb_{it} + \beta_6 ReviewScores_{it} + \beta_7 Amenities_{it} \\
&+ \beta_8 ControlVariables_{it} + \epsilon_{it} \qquad (3.2) \\
AreaOccRate_{it} = c &+ \beta_1 AirbnbSupply_{it} + \beta_2 + \beta_3 Price_{it} + \beta_4 SecurityDeposit_{it} \\
&+ \beta_5 OccRateAirbnb_{it} + \beta_6 ReviewScores_{it} + \beta_7 Amenities_{it} \\
&+ \beta_8 ControlVariables_{it} + \epsilon_{it} \qquad (3.3)
\end{aligned}
$$

Where:

$AreaRevPar_{it}$ is the average monthly revenue per available room of hotels in an area observed by the Airbnb i and at a time t, $AreaAvPricer_{it}$ is the monthly average price of a room of hotels in an area observed by the Airbnb i and at a time t, $AreaOccRate_{it}$ is the monthly average occupancy rate of hotels in an area observed by the Airbnb i and at a time t. Average hotels RevPar is the main dependent variable in this study. We also tested the model on three other monthly dependent variables [9] $ThreeRevPar_{it}$, $FourRevPar_{it}$ and $FiveRevPar_{it}$) which represent the average RevPar on hotels depending on hotel category level (3-,4- and 5-star hotels). These average RevPar are not for each area analysed and are for the entire area of Brussels. All these dependent variables concern monthly financial hotel performances and expressed in euro.

$AirbnbSupply_{it}$ is Airbnb accommodations number per zone in the zone of the Airbnb accommodation i and at a time t. $PrivateRoom_{it}$ is a dummy variable reflecting Airbnb i type of room at a time t, taking the form 1 if the airbnb is a private room and 0 otherwise, $Price_{it}$ is the location price in euro of an Airbnb accommodation i and at a time t for one night, , $SecurityDeposit_{it}$ represents security deposit amount in euro the guest needs to give to the host to be able to stay in the Airbnb i at a time t. $ReviewScores_{it}$ is the score of user satisfaction for the Airbnb i at a time t, $ReviewsPerMonth_{it}$ is the number of reviews the Airbnb i had to face at a time t. $OccRateAibnb_{it}$ is the monthly occupancy rate of the Airbnb i at a time t computed as explained in section Measures. $Amenities_{it}$ is a bunch of dummies variables where $Amenities = 1$ if the Airbnb i at a time t has this amenity. In this study, we control for the presence of a kitchen, pet friendly possibility, wheelchair access, free parking available for the guest(s), long-term stay possibility, 24-hour check-in, private entrance, smoking inside possibilities, gym or again a swimming pool. These variables represent the explanatory variables of our models. Interaction terms will be constructed by the authors with other variables as $PenetrationRate$, which represents the penetration rate of each room types Airbnb accommodations in total Airbnb accommodations and $EntireHome$ which is a dummy variable reflecting Airbnb i type of room at a time t, taking the form 1 if the airbnb is an entire home or apartment and 0 otherwise.

$ControlVariables_{it}$ represent a bunch of control variables: (i) two control variables for tourism flow ($NightLeisureMonth$ and $NightMeetingMonth$) which are tourism competitiveness indicators representing the number of booked nights per month in Brussels from foreign and domestic customers classified per reason to stay (leisure and business) [Dupeyras et al., 2013], (ii) dummies variables for each time period considered controlling for differences across time and (iii) dummies variables for each area considered in this study controlling for environment differences.

[9] $ThreeRevPar$, $FourRevPar$ and $FiveRevPar$ are average for all hotels considered in the sample but are not average for hotels per area considered as $AvRevPar$, $AreaAvPrice$ and $AreaOccRate$.

To test Hypothesis 6, authors construct interaction terms in correlated random-effects model between variables. Each model can test for one interaction term between two variables, reflecting combined effect on dependent variable. In this study, we combine Airbnb dummies variables representing Airbnb accommodation amenities to asses this combined effect on the average hotel RevPar.

4 Results

4.1 Correlation matrix and regression results

Table 4.1: Matrix of correlation
Source : Stata

Variables	1	2	3	4	5	6	7	8	9	10
(1) NbrAirbnbZone	1									
(2) dPrivateRoom	-0,11	1								
(3) Price	0,136	-0,28	1							
(4) SecurityDeposit	0,044	-0,16	0,205	1						
(5) OccRateAirbnb	0,033	-0	-0,05	-0,09	1					
(6) ReviewScores	0,012	0,015	0,021	0,024	0,074	1				
(7) dKitchen	0,008	-0,27	0,036	0,078	-0,07	-0	1			
(8) dPetAllowed	-0,02	0,074	-0,02	-0,05	-0,02	0,017	-0,02	1		
(9) dOutdoorSpace	-0,03	0,016	0,02	0,012	0,028	0,048	0,004	-0,01	1	
(10) dWheelchairAccess	-0,04	-0,1	0,112	0,096	-0,04	0,033	0,082	-0,03	-0,07	1
(11) dFreeParking	-0,13	0,015	0,027	0,038	0,014	0,036	0,004	0,069	0,053	0,071
(12) dLuggageDropoff	0,035	-0,07	0,089	0,043	0,092	0,06	0,019	-0,01	0,127	0,019
(13) d24hourCheck	0,057	-0,07	0,052	0,07	-0	0,012	0,035	-0,02	-0,01	0,037
(14) dPrivateEntrance	0,018	-0,14	0,143	0,048	0,058	0,027	0,001	-0,05	0,074	0,075
(15) dSmoking	-0,06	0,165	-0,14	-0,1	-0,04	-0,08	0,048	0,206	0,037	-0,09
(16) dGym	-0,05	0,039	0,016	-0,01	-0,02	0,01	-0,03	0,072	0,048	0,04
(17) dPool	0,013	0,042	0,006	0,003	-0,02	0,013	0,011	0,107	-0,01	0,045
(18) NightLeisureMonth	0,08	0,003	0,007	-0,01	0,005	0,001	-0	0,008	0,001	0,005
(19) NightMeetingMonth	0,053	-0	0,01	0,006	0,005	-0,01	0,003	-0	0,008	0,004

Variables	11	12	13	14	15	16	17	18	19
(1) NbrAirbnbZone									
(2) dPrivateRoom									
(3) Price									
(4) SecurityDeposit									
(5) OccRateAirbnb									
(6) ReviewScores									
(7) dKitchen									
(8) dPetAllowed									
(9) dOutdoorSpace									
(10) dWheelchairAccess									
(11) dFreeParking	1								
(12) dLuggageDropoff	0,081	1							
(13) d24hourCheck	-0,04	0,14	1						
(14) dPrivateEntrance	-0,01	0,157	-0,02	1					
(15) dSmoking	-0	-0,05	0	-0,12	1				
(16) dGym	0,128	0,012	0,006	0,025	0,014	1			
(17) dPool	0,105	-0	0,067	0,022	-0	0,216	1		
(18) NightLeisureMonth	-0	-0,01	-0	0	-0	0,001	0,001	1	
(19) NightMeetingMonth	0,004	0,009	-0,02	0,025	-0,01	0,001	-0	-0,13	1

Table 4.2: Regression results on hotel average AreaRevPar
Source : Stata

AreaRevPar	**Coef.**	**St.Err.**	**t-value**	**p-value**	**[95% Conf**	**Interval]**	**Sig**
AirbnbSupply	0.057	0.001	59.84	0.000	0.055	0.059	***
dPrivateRoom	-0.819	0.408	-2.01	0.045	-1.618	-0.020	**
Price	-0.003	0.002	-2.29	0.022	-0.006	-0.001	**
SecurityDeposit	0.001	0.000	3.68	0.000	0.000	0.002	***
OccRateAirbnb	0.038	0.057	0.66	0.511	-0.074	0.149	
ReviewScores	-0.019	0.009	-2.08	0.037	-0.036	-0.001	**
dKitchen	0.109	0.378	0.29	0.772	-0.631	0.850	
dPetAllowed	-0.131	0.397	-0.33	0.742	-0.909	0.648	
dOutdoorSpace	0.327	0.365	0.90	0.370	-0.389	1.042	
dWheelchairAccess	0.077	0.317	0.24	0.807	-0.544	0.698	
dFreeParking	0.789	0.276	2.86	0.004	0.249	1.329	***
dLuggageDropoff	0.168	0.175	0.96	0.335	-0.174	0.511	
d24hourCheck	0.378	0.462	0.82	0.414	-0.528	1.283	
dPrivateEntrance	0.075	0.341	0.22	0.825	-0.592	0.743	
dSmoking	0.151	0.341	0.44	0.658	-0.518	0.819	
dGym	0.632	0.783	0.81	0.420	-0.903	2.167	
dPool	2.369	3.831	0.62	0.536	-5.139	9.877	
NightLeisureMonth	0.000	0.000	-273.17	0.000	0.000	0.000	***
NightMeetingMonth	0.000	0.000	153.29	0.000	0.000	0.000	***
mAirbnbSupply	0.007	0.001	5.09	0.000	0.004	0.009	***
mdPrivateRoom	0.803	0.412	1.95	0.051	-0.003	1.610	*
mPrice	0.004	0.002	2.35	0.019	0.001	0.007	**
mSecurityDeposit	-0.001	0.000	-3.47	0.001	-0.002	0.000	***
mOccRateAirbnb	-0.083	0.074	-1.11	0.265	-0.228	0.063	
mReviewScores	0.017	0.009	1.86	0.063	-0.001	0.036	*
mdKitchen	-0.184	0.390	-0.47	0.636	-0.949	0.580	
mdPetAllowed	0.045	0.404	0.11	0.911	-0.747	0.837	
mdOutdoorSpace	-0.353	0.389	-0.91	0.365	-1.115	0.410	
mdWheelChairAccess	-0.085	0.320	-0.26	0.792	-0.712	0.543	
mdFreeParking	-0.787	0.287	-2.74	0.006	-1.350	-0.224	***
mdLuggageDropoff	-0.188	0.185	-1.02	0.308	-0.550	0.174	
md24hourCheck	-0.391	0.466	-0.84	0.401	-1.305	0.522	
mdPrivateEntrance	-0.042	0.346	-0.12	0.902	-0.720	0.635	
mdSharedRoom	-0.098	0.282	-0.35	0.729	-0.651	0.455	
mdSmoking	-0.157	0.348	-0.45	0.652	-0.840	0.526	
mdGym	-0.884	0.807	-1.09	0.274	-2.467	0.698	
mdPool	-2.247	3.871	-0.58	0.562	-9.834	5.341	
mNightLeisureMonth	0.000	0.000	-1.62	0.105	0.000	0.000	
mNightMeetingMonth	0.000	0.000	0.36	0.719	0.000	0.000	
yRogierBotanique	7.827	0.577	13.57	0.000	6.697	8.957	***
yBrusselsAirport	25.605	0.984	26.01	0.000	23.675	27.535	***
yGrandPlaceEnvirons	-2.177	0.153	-14.23	0.000	-2.477	-1.877	***
yMidiLemonnier	8.275	0.485	17.07	0.000	7.324	9.225	***
yQuartierEuropéeen	2.618	0.064	40.72	0.000	2.492	2.744	***
y201804	10.418	0.188	55.46	0.000	10.049	10.786	***
y201805	-4.418	0.182	-24.27	0.000	-4.774	-4.061	***
y201807	1.830	0.164	11.19	0.000	1.510	2.151	***
y201808	9.970	0.170	58.53	0.000	9.636	10.304	***
y201809	-12.891	0.153	-84.06	0.000	-13.191	-12.590	***
y201810	1.625	0.163	9.97	0.000	1.306	1.945	***
y201811	-12.238	0.155	-79.05	0.000	-12.541	-11.934	***
y201812	1.671	0.149	11.24	0.000	1.380	1.962	***
y201901	-46.302	0.296	-156.36	0.000	-46.883	-45.722	***
y201902	-37.689	0.249	-151.55	0.000	-38.176	-37.201	***
y201903	-19.841	0.147	-135.12	0.000	-20.129	-19.553	***
y201904	-7.807	0.131	-59.81	0.000	-8.063	-7.551	***

Table 4.2: Regression results on hotel average AreaRevPar
Source : Stata

AreaRevPar	**Coef.**	**St.Err.**	**t-value**	**p-value**	**[95% Conf**	**Interval]**	**Sig**
y201905	-1.783	0.112	-15.88	0.000	-2.003	-1.563	***
y201906	-1.907	0.114	-16.78	0.000	-2.130	-1.684	***
Constant	99.670	1.985	50.21	0.000	95.780	103.561	***

Mean dependent var	97.704	SD dependent var	21.007
Overall r-squared	0.943	Number of obs	54.512.000
Chi-square	896.019.046	Prob > chi2	0.000
R-squared within	0.932	R-squared between	0.967

$***p < 0.01$, $**p < 0.05$, $*p < 0.1$

4.2 Results explanation

Most hypotheses concern the hotel average revenue per available room which is our main dependent variable. Hypotheses concerning other dependent variables as the average daily rate, the average occupancy rate per hotel category or hotel average RevPar per hotel category level would be analysed through complementary regression results. The interaction terms constructed by the authors are also analysed through complementary regression results.

Hypothesis 1 : Airbnb supply has a negative impact on the hotel average RevPar. Hypothesis 1 states Airbnb supply, through Airbnb accommodations numbers per zone has a negative impact on the hotel average RevPar. This hypothesis is rejected. Indeed, If Airbnb supply increases in a zone (+100 accommodations from any room type), hotel average RevPar in the same zone is impacted by 5,7 €[10] All the hotels financial and occypancy data are available in appendix C.5.1. This significant result (H1) doesn't support for the conclusion for the presence of a substitution effect between Airbnb accommodations and hotel rooms in Brussels but it supports the conclusion for a complementary role of Airbnb in the lodging industry. Some research has found the same conclusion [Strømmen-Bakhtiar and Vinogradov, 2019]. Further analysis will be conducted below on complementary regression results to assess Airbnb supply impact on different average hotel RevPar depending on hotel category level, represented in Belgium by the number of stars a hotel has (3-, 4- and 5-stars) through the hypothesis 1a and another way to prove substitution effect or complementary effect between Airbnb accommodations and hotel rooms through hypothesis 2.

Hypothesis 5 : The amount of a security deposit for Airbnb accommodation has a positive impact on hotel average RevPar. Through regression results in Table 4.2, authors can confirm the hypothesis 3 with a positive and significative impact from security deposit amount on hotel average RevPar. However, if the amount of security deposit increases by 100 € by average in a zone, the hotel average RevPar within the zone is impacted positively by 0,1 €. It confirms a security deposit has negative impact when consumers make a choice between an hotel room and an Airbnb accommodation and it also confirms a substitution effect between Airbnb and hotels. Indeed, because a security deposit only exists for Airbnb accommodations and not for hotel rooms and that the significant effect impacts positively the hotel average RevPar. Airbnb and hotels are considered by consumers as substitute. As said by Benjamin et al. [1998], consumers who are not able to pay the security deposit amount for an Airbnb rental are led to turn to a cheaper option. Indeed, people looking for an accommodation are more likely to delete Airbnb possibility when the accommodation is under a security deposit and choose a hotel room to stay or another Airbnb accommodation. This significant effect (H5) supports the conclusion for a substitution effect between Airbnb and hotels in Brussels, allowing Airbnb to be a disruptive innovation. Nevertheless, the effect for an 10% increase is quite low so the contribution of the acceptance of hypothesis 5 to the hypothesis of substitution effect put forward by the authors is also quite low.

In Airbnb data, there is more than 60% accommodations having no security deposit in Brussels[11]. The security amount is more present for entire houses or apartments. Indeed, the average security deposit amount is 151.81 € for an entire house or apartment type but for private room, the average is 50,75 €. For the shared room, this amount is on average only 21.42 €.

Hypothesis 7 : The presence of amenities in Airbnb accommodations impact negatively hotel average RevPar.

[10] This is an average for all areas considered.

[11] Airbnb data mentioned corresponds to Airbnb data used in this study. For more details, see Descriptive variables

The hypothesis 7 stipulates the presence of amenities within Airbnb accommodations impact negatively hotel average RevPar. Only the presence of a free parking which is considered in the amenities has a significant effect on average hotel RevPar. The hypothesis is rejected for the amenity free parking and cannot be tested for other amenities because of non-significant effects.

4.3 Further analysis

4.3.1 Further regression results

Table 4.3: Regression results on hotels average AreaAvPrice, average AreaOccRate and average hotels RevPar under category level
Source : Stata

VARIABLES	(1) AreaAvPrice	(2) AreaOccRate	(3) ThreeRevPar	(4) FourRevPar	(5) FiveRevPar
AirbnbSupply	0.0555***	9.52e-05***	-0.00189***	0.00669***	0.0143***
	(0.000993)	(4.74e-06)	(0.000323)	(0.000283)	(0.000289)
dPrivateRoom	-0.746*	-0.00304	-0.0843	-0.158	-0.0981
	(0.423)	(0.00202)	(0.138)	(0.121)	(0.122)
Price	-0.00399**	-1.65e-05**	0.000840	0.000584	-3.80e-05
	(0.00158)	(7.53e-06)	(0.000513)	(0.000450)	(0.000452)
SecurityDeposit	0.00111***	4.68e-06***	6.94e-06	2.67e-05	4.87e-05
	(0.000284)	(1.35e-06)	(9.23e-05)	(8.08e-05)	(8.13e-05)
OccRateAirbnb	0.00639	0.000286	-0.00184	0.00206	0.00530
	(0.0592)	(0.000282)	(0.0192)	(0.0169)	(0.0169)
ReviewScores	-0.0232**	-6.70e-05	-7.34e-05	-0.00449*	-0.00994***
	(0.00935)	(4.46e-05)	(0.00304)	(0.00267)	(0.00267)
dKitchen	-0.0228	0.00134	-0.320**	-0.292***	-0.177
	(0.392)	(0.00187)	(0.128)	(0.112)	(0.112)
dPetAllowed	0.108	-0.00206	-0.0329	0.00257	0.00497
	(0.412)	(0.00197)	(0.134)	(0.117)	(0.118)
dOutdoorSpace	0.426	0.000937	0.122	0.352***	0.555***
	(0.379)	(0.00181)	(0.123)	(0.108)	(0.109)
dWheelchairAccess	0.0569	0.000357	0.0897	-0.0571	-0.207**
	(0.329)	(0.00157)	(0.107)	(0.0937)	(0.0942)
dFreeParking	1.211***	2.60e-05	0.140	0.343***	0.439***
	(0.286)	(0.00136)	(0.0930)	(0.0815)	(0.0820)
dLuggageDropoff	0.186	0.000146	0.0918	0.125**	0.168***
	(0.181)	(0.000866)	(0.0590)	(0.0517)	(0.0520)
d24hourCheck	0.368	0.00195	-0.103	0.0312	0.114
	(0.479)	(0.00229)	(0.156)	(0.137)	(0.137)
dPrivateEntrance	-0.0671	0.00209	0.105	0.132	0.123
	(0.354)	(0.00169)	(0.115)	(0.101)	(0.101)
dSmoking	-0.138	0.00181	-0.0380	-0.149	-0.189*
	(0.354)	(0.00169)	(0.115)	(0.101)	(0.101)
dGym	0.708	0.00182	-0.0102	-0.0335	-0.0258
	(0.813)	(0.00388)	(0.264)	(0.232)	(0.233)
dPool	5.783	-0.00422	0.323	0.970	1.449
	(3.975)	(0.0190)	(1.293)	(1.133)	(1.136)
NightLeisureMonth	-0.000433***	-6.51e-07***	-0.000305***	-0.000406***	-0.000485***
	(1.64e-06)	(7.85e-09)	(5.35e-07)	(4.68e-07)	(4.71e-07)
NightMeetingMonth	0.000294***	1.84e-06***	0.000322***	0.000427***	0.000500***
	(2.69e-06)	(1.29e-08)	(8.76e-07)	(7.67e-07)	(7.70e-07)
mAirbnbSupply	0.00639***	5.35e-06	0.00242***	0.00216***	0.00247***
	(0.00135)	(6.47e-06)	(0.000441)	(0.000386)	(0.000448)
mdPrivateRoom	0.702	0.00324	0.0801	0.145	0.0687
	(0.427)	(0.00204)	(0.139)	(0.122)	(0.124)
mPrice	0.00418**	1.77e-05**	-0.000791	-0.000511	0.000137
	(0.00164)	(7.84e-06)	(0.000534)	(0.000468)	(0.000490)
mSecurityDeposit	-0.00112***	-4.54e-06***	-1.88e-05	-3.65e-05	-5.44e-05
	(0.000297)	(1.42e-06)	(9.65e-05)	(8.46e-05)	(8.88e-05)
mOccRateAirbnb	-0.0283	-0.000572	-0.00704	-0.00348	0.00266
	(0.0770)	(0.000368)	(0.0251)	(0.0220)	(0.0267)

Table 4.3: Regression results on hotels average AreaAvPrice, average AreaOccRate and average hotels RevPar under category level
Source : Stata

VARIABLES	(1) AreaAvPrice	(2) AreaOccRate	(3) ThreeRevPar	(4) FourRevPar	(5) FiveRevPar
mReviewScores	0.0224**	6.31e-05	-0.000932	0.00354	0.00931***
	(0.00975)	(4.65e-05)	(0.00317)	(0.00278)	(0.00289)
mdKitchen	-0.0662	-0.00156	0.322**	0.281**	0.126
	(0.405)	(0.00193)	(0.132)	(0.115)	(0.120)
mdPetAllowed	-0.210	0.00195	0.0142	-0.0307	-0.0573
	(0.419)	(0.00200)	(0.136)	(0.120)	(0.122)
mdOutdoorSpace	-0.485	-0.000848	-0.139	-0.377***	-0.621***
	(0.404)	(0.00193)	(0.131)	(0.115)	(0.122)
mdWheelChairAccess	-0.0487	-0.000418	-0.0930	0.0598	0.225**
	(0.332)	(0.00159)	(0.108)	(0.0948)	(0.0964)
mdFreeParking	-1.243***	0.000195	-0.148	-0.356***	-0.467***
	(0.298)	(0.00142)	(0.0970)	(0.0850)	(0.0889)
mdLuggageDropoff	-0.249	-2.88e-05	-0.101	-0.151***	-0.230***
	(0.192)	(0.000914)	(0.0623)	(0.0546)	(0.0578)
md24hourCheck	-0.387	-0.00189	0.105	-0.0292	-0.120
	(0.484)	(0.00231)	(0.157)	(0.138)	(0.140)
mdPrivateEntrance	0.0964	-0.00195	-0.106	-0.136	-0.124
	(0.359)	(0.00171)	(0.117)	(0.102)	(0.104)
mdSharedRoom	-0.296	0.00127	-0.0466	-0.0413	-0.0557
	(0.293)	(0.00140)	(0.0953)	(0.0835)	(0.114)
mdSmoking	0.114	-0.00179	0.0357	0.147	0.190*
	(0.361)	(0.00173)	(0.118)	(0.103)	(0.106)
mdGym	-0.932	-0.00273	-0.0232	0.0183	0.0352
	(0.838)	(0.00400)	(0.273)	(0.239)	(0.248)
mdPool	-5.536	0.00356	-0.267	-0.907	-1.375
	(4.018)	(0.0192)	(1.307)	(1.145)	(1.164)
mNightLeisureMonth	-2.22e-07	-2.78e-08*	-9.24e-07	4.93e-07	1.33e-06
	(3.03e-06)	(1.45e-08)	(9.87e-07)	(8.65e-07)	(1.02e-06)
mNightMeetingMonth	8.89e-06	1.97e-08	-1.41e-06	6.67e-06***	1.42e-05***
	(6.46e-06)	(3.08e-08)	(2.10e-06)	(1.84e-06)	(2.12e-06)
yRogierBotanique	0.589	0.0466***	0.227	3.534***	6.667***
	(0.598)	(0.00286)	(0.195)	(0.171)	(0.196)
yBrusselsAirport	23.18***	0.0409***	0.366	6.057***	11.50***
	(1.022)	(0.00488)	(0.332)	(0.291)	(0.336)
yGrandPlaceEnvirons	-9.269***	0.0431***	-0.0318	-0.850***	-1.663***
	(0.159)	(0.000758)	(0.0516)	(0.0453)	(0.0552)
yMidiLemonnier	-2.092***	0.0761***	0.190	2.999***	5.695***
	(0.503)	(0.00240)	(0.164)	(0.143)	(0.165)
yQuartierEuropéen	11.27***	-0.0471***	0.0109	-0.000487	-0.0116
	(0.0667)	(0.000319)	(0.0217)	(0.0190)	(0.0277)
y201804	14.33***	0.0143***	4.205***	5.833***	4.264***
	(0.195)	(0.000930)	(0.0634)	(0.0556)	(0.0567)
y201805	-4.286***	0.00716***	-5.440***	-8.324***	-14.45***
	(0.189)	(0.000902)	(0.0615)	(0.0538)	(0.0550)
y201807	-3.358***	0.0512***	-3.870***	-5.754***	9.684***
	(0.170)	(0.000810)	(0.0552)	(0.0484)	(0.0493)
y201808	3.570***	0.0590***	5.892***	5.110***	5.237***
	(0.177)	(0.000844)	(0.0575)	(0.0504)	(0.0511)
y201809	-15.89***	0.0101***	-11.51***	-13.42***	-22.27***
	(0.159)	(0.000760)	(0.0518)	(0.0454)	(0.0461)
y201810	-0.289*	0.00594***	-4.916***	-5.186***	0.672***
	(0.169)	(0.000808)	(0.0550)	(0.0482)	(0.0492)
y201811	-15.11***	-0.00422***	-16.24***	-16.40***	-19.68***
	(0.161)	(0.000767)	(0.0523)	(0.0458)	(0.0466)
y201812	5.817***	-0.0111***	-5.189***	-5.929***	-3.482***

Table 4.3: Regression results on hotels average AreaAvPrice, average AreaOccRate and average hotels RevPar under category level
Source : Stata

VARIABLES	(1) AreaAvPrice	(2) AreaOccRate	(3) ThreeRevPar	(4) FourRevPar	(5) FiveRevPar
	(0.154)	(0.000736)	(0.0502)	(0.0440)	(0.0447)
y201901	-35.88***	-0.114***	-37.90***	-43.59***	-52.63***
	(0.307)	(0.00147)	(0.1000)	(0.0876)	(0.0882)
y201902	-35.81***	-0.0450***	-29.84***	-35.55***	-49.64***
	(0.258)	(0.00123)	(0.0839)	(0.0736)	(0.0741)
y201903	-15.56***	-0.0443***	-17.38***	-19.51***	-28.30***
	(0.152)	(0.000727)	(0.0496)	(0.0434)	(0.0439)
y201904	-6.995***	-0.0156***	-8.068***	-10.48***	-15.34***
	(0.135)	(0.000647)	(0.0441)	(0.0386)	(0.0391)
y201905	4.731***	-0.0392***	-0.998***	-3.122***	-9.249***
	(0.116)	(0.000556)	(0.0379)	(0.0332)	(0.0335)
y201906	-4.041***	0.00284***	-4.175***	-3.647***	0.815***
	(0.118)	(0.000563)	(0.0384)	(0.0336)	(0.0338)
Constant	152.6***	0.463***	106.9***	121.4***	141.1***
	(2.060)	(0.00983)	(0.670)	(0.587)	(0.654)
Observations	54,512	54,512	54,512	54,512	54,512
Number of id	5,124	5,124	5,124	5,124	5,124

Hypothesis 1A: The negative impact from Airbnb supply on hotel average RevPar decrease as hotel category increases. The hypothesis 1A stipulates that negative impact from Airbnb supply on hotel average RevPar decrease as hotel category increases. Authors have proven there is a positive impact of Airbnb supply on hotel average RevPar per zone through the reject of hypothesis 1. Through complementary regression results, the effect of Airbnb supply on the hotel average RevPar per category level (number of stars) is significant. For 3-stars hotels, Airbnb supply increasing by 100 accommodations from any type in a zone has a negative impact on all the Brussels hotel average RevPar by a decrease of 0,19 €. If the Airbnb whereas for 4- and 5-stars hotels, Airbnb supply has a positive impact 4.3. Indeed, for the same increase level in Airbnb supply, the RevPAR of the 4-stars hotels rises by 0,67 € and that of 5-stars hotels rises by 1,43 €.

Authors can't accept the hypothesis so the hypothesis 1a is rejected. It confirms the conclusion of the support of complementarity between Airbnb and hotel rooms for the 4- and 5-stars hotel but not for the 3-stars hotels. Hotel value appropriation can profit from value creation by Airbnb.

Hypothesis 2: Airbnb price has a positive impact on hotels average occupancy rate. Through complementary regression results, the effect from Airbnb accommodations prices on hotels average occupancy rate is significant at a level of 5% and negative but nearly equal to zero. It confirms the conclusion of the hypothesis 1 Airbnb and hotels are complementary in the accommodation market. Authors reject the hypothesis 2.

Hypothesis 7A: The negative effect from the presence of an amenity in Airbnb accommodations is less and less present as hotels category2 level increases. For the reason that hypothesis7 has been rejected because of the few significant effects of the presence of an amenity in housing Airbnb on average hotel RevPar, the hypothesis 7A must be rejected. Indeed, in the complementary regression results, effects from amenities presence on the average hotel RevPar according to category hotel level are not significant for all three levels of the hotel category. Authors must reject the hypothesis 7A.

4.3.2 Interaction terms

Hypothesis 6 : Airbnb can benefit from a compensation effect by following another standard norm than hotel industry which can be translated as a negative impact on hotel financial variables by Airbnb pursuing the achievement of another norm (outdoor space) than standard hotel industry (luggage drop-off). To test this hypothesis, authors constructed interaction terms between some dummy variables reflecting the presence of amenities (= 1) or not (= 0). To reminder, some amenities are considered in the hotel industry as standard norms in hotel average supply (3-stars hotels) which are followed by Airbnb accommodations part as luggage drop-off, free parking or 24hour check-in and some amenities which are followed by Airbnb accommodations which are not considered in the hotel industry as standard norms. The regression results are available in Appendix B

Authors formed some interaction terms in such number of models because each model can accept only one interaction term. The interaction terms are the following ones:

- dOutdoorSpace*d24hourCheck
- dSmoking*dLuggageDropOff
- dPetAllowed*dFreeParking
- dKitchen*dFreeParking
- dPrivateEntrance*d24hourCheck
- dSmoking*dFreeParking
- dOutdoor*dFreeParking
- dKitchen*dLuggageDropoff
- dPetAllowed*d24hourCheck

Through our interaction term results, the hypothesis 6 is rejected because each interaction term has a non-significant effect on the hotel average RevPar per zone. The only significant result which concerns the hypothesis is the effect of a free parking presence (standard norm for hotel industry) combined with the absence of an extra-norm (PetAllowed and Kitchen).

Indeed, the effect of free parking presence in Airbnb accommodations without the presence of a kitchen for the guests impact positively the average hotel RevPar. Another fact interesting, the combined effect from the presence of a kitchen and the presence of a free parking impacts significantly and positively the hotel average RevPar. The presence of a free parking without the possibility to welcome pets in the Airbnb accommodations impact significantly and positively the hotel average RevPar.

Hypothesis 4 : The combined effect from Airbnb price and Airbnb occupancy rate impact negatively hotel average RevPar. The analysis trought the regression has shown that the combined effect from Airbnb price and Airbnb occupancy rate is significant and impact positively hotel average RevPar (Graph 4.1 and more details in Descriptive variables). This combined effect measure the impact of Airbnb RevPar. Authors reject hypothesis 4. This reject doesn't support for the conclusion of substitution effect between Airbnb and hotels. If Airbnb RevPar for a zone increases by 10 €, hotels average RevPar within the zone increases by 0,05 €. Airbnb value capture can't increase from impacting negatively hotel value appropriation.

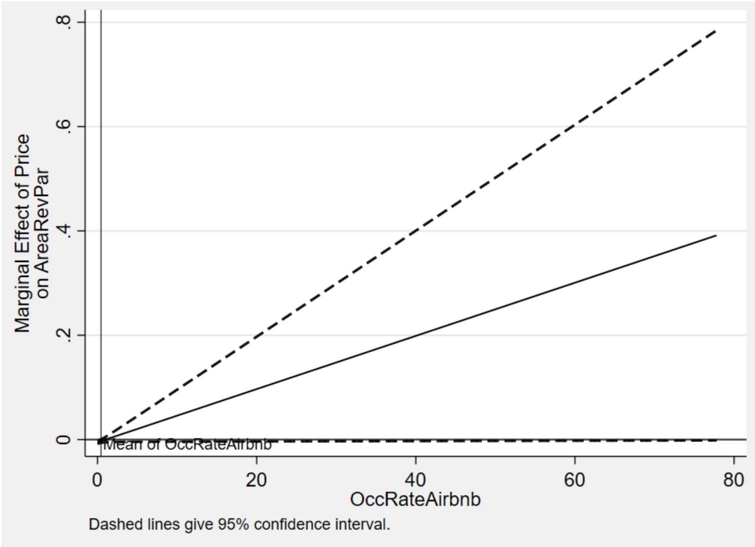


Figure 4.1: *The positive effect from combined Airbnb price and Airbnb occupancy rate on the hotel average RevPar.*
Source : Stata

Hypothesis 1A: The joined effect from Penetration Rate and the private room type has a negative impact on average hotel RevPar The joined effect constructed as an interaction effect between "dPrivateRoom" and "PenetrationRate" has a significant and negative impact on average hotel RevPar. If the penetration rate of private room type in Brussels increase by one percentage point, the hotel average RevPar in Brussels decrease by 1,149 €. It supports the conclusion Airbnb and hotel rooms are substitute but concerning only private room type. The authors accept hypothesis 1A at a significant level of 5%. Airbnb creates value with a resource-based view of the firm thanks to being a disruptive innovation in lodging market. By being a disruptive innovation, Airbnb competes hotel room but from just one room type accommodation proposed by Airbnb, the private room type and impact hotel value appropriation in Brussels negatively.

Hypothesis 1B: The joined effect from Entire home/apartment room type and Penetration Rate has a negative impact on average hotel RevPar The joined effect constructed as an interaction effect between *dPrivateRoom* and *PenetrationRate* has a significant and positive impact on average hotel RevPar. If the penetration rate of entire home type in Brussels increases by one percentage point, the hotel average RevPar in Brussels increase by 1,51 €. The authors reject hypothesis 1B and support through this reject for complementarity in lodging market in Brussels between Airbnb and hotel rooms but only concerning entire home/apartment type. Airbnb creates value by increase accommodations of the entire home/apartment for all stakeholders and the market. Hotel value appropriation benefits from this effect and the value capture for hotel rooms increases as observed in regression results. The coefficients from both interaction terms can be compared thanks to their non-overlapping confidence intervals and thanks to the presence of similarities in the coefficients of the other explanatory variables in the two models.

Considering hotel average RevPar is constructed by the multiplication of the hotel average occupancy rate and of the average daily rate of a room[12], it would be interesting to test these two interaction terms on these hotel variables, allowing to decompose the effect from these two interaction terms representing a Airbnb supply diversity side on RevPar. These tests are available in Descriptive variables. By these tests, authors remarked most of the effect concerns the average daily rate of a room and this effect is strong negative for private room type and strong positive

[12]The average daily rate is also called in this study by the average price of a room.

for entire homes/apartments. The effect on hotel average occupancy rate is negative and very weak from both private rooms supply increase and entire homes/apartments supply increase.

It's important to shade the conclusions from hypotheses 1, 1B and 1C. All of these three hypotheses concern Airbnb supply presence impact on hotel average RevPar. The hypotheses 1 and 1B support for complementarity between Airbnb accommodations and hotel rooms whereas the hypothesis 6a plaid for substitution effect between these two housing options. In our sample, 70,72% of Airbnb accommodations are entire home or apartments and 28,42% are private room[13]. Authors suppose the positive impact on average hotel RevPar from increasing the number of entire home/apartments has surpassed the negative impact from increasing the number of private rooms in the impact of Airbnb supply all confused accommodations.

[13] Authors didn't consider Airbnb supply impact concerning share room type because of their weak representativity in the sample (0,86%) but regression results from interaction term between "dSharedRoom"and "PenetrationRate" are available in Descriptive variables

5 Discuss

Results from assessing Airbnb impact on average hotel RevPar point out the fact Airbnb accommodations and hotel rooms are complementary if authors consider Airbnb supply as Airbnb supply for all types of accommodation. Hotel value appropriation increases as Airbnb supply increases in terms of numbers. The positive impact from Airbnb RevPar on hotel average RevPar also identifies hotel rooms and Airbnb accommodations as complementary. Accepting hypothesis5 support for the conclusion of the substitution. Indeed, by having a possible constraint with security deposit amount, consumers can turn to hotel rooms, but this increase in hotel value appropriation is quite low. By considering each type of accommodations, authors remark that private rooms are substitute with hotel rooms whereas entire homes and apartments are not substitute. Indeed, Airbnb by increasing private rooms supplies impacts negatively hotel value appropriation in Brussels and by increasing entire homes and apartments supply creates market value that hotel value appropriation benefits from. Concerning assumptions on amenities, no significant effect has been made through study estimates to allow authors some conclusion about amenities presence in Airbnb accommodations. Airbnb is considered as a disruptive innovation in the lodging market through its platform, but only private rooms are substitute to hotel rooms. Airbnb impacts negatively value hotel appropriation if it concerns private rooms but if it concerns entire homes, it increases hotel value appropriations. Airbnb creates value for hotels but destroys too. By being a disruptive innovation, Airbnb created a competitive advantage for itself thanks to a resource-based view of the firm but the authors assume with these results that Airbnb did not achieve the same quality of service as hotels, attracting low-end customers except for private rooms.

5.1 Litterature Contribution

Airbnb supply There is no consensus about impact from Airbnb supply or presence on hotel RevPar. On one hand, Strømmen-Bakhtiar and Vinogradov [2019] found a positive effect between the presence of Airbnb and the number of rooms and nights sold by the hotels. On the other hand, a study conducted by HVS Consulting [2015] demonstrated the significant negative impact of Airbnb on the hotel market in New York. The U.S. market was also addressed by Zervas et al. [2017] and Farronato and Fradkin [2018], which highlighted a significant negative impact of Airbnb on hotel revenues. In the study seek by HVS Consulting [2015], they arrived at this conclusion by looking at Airbnb's performance figures in New York and considering that each reservation made in an Airbnb is one less reservation for hotels in the city. The figures put forward by this study therefore show a huge impact of Airbnb on the hotel market. Faced with this contradiction in information, the authors wanted to analyse the situation in Brussels and compare the results obtained in terms of supply-side impact with the results of the literature review. An overall small positive effect of Airbnb's offer on hotel performance has been demonstrated through this study. This supports for the complementarity of Airbnb and the hotels. However, this effect is nuanced for low-end hotels. Indeed, these are slightly negatively impacted by the presence of Airbnb. Four- and five-star hotels, on the other hand, are positively impacted.

Room type By differentiating Airbnb's offer by type of accommodation, authors have found significant impact from increasing Airbnb supply on hotel average RevPar in Brussels. Through the regression results, authors have found that private rooms are substitute to hotel rooms, impacting negatively hotel value appropriation whereas entire homes or apartments are complementary to hotel rooms, allowing an increase in hotel value appropriation. Airbnb is recognised by the authors as a disruptive innovation even if only private rooms propose the same service/quality than hotel rooms.

Security deposit Some research has been made on security deposit and the impact can have on accommodation choice. The amount of a security deposit is a barrier for renters [Benjamin et al., 1998] but no research has been made on the impact from security deposit amount on the accommodation choice between Airbnb accommodations and hotel rooms specifically. By increasing the amount, the security deposit can become a barrier for guests and change their accommodation choice by selecting another Airbnb accommodation or a hotel room. By selecting hotel rooms, Airbnb guests favour value capture for hotels. Security deposit amount for an Airbnb accommodation could benefit hotel average RevPar even if the effect is quite low.

5.2 Involvement for practitioners

The details provided by this study on the impact of Airbnb on the hotel market in Brussels may be useful for a number of stakeholders. By highlighting a greater impact of private rooms on hotel revenues, it can guide the taxation of Airbnb accommodation by the city of Brussels. Legislating the collaborative economy has been an important issue since the rise of the collaborative economy. Given the value created by this new means of short-term accommodation, the cities in which Airbnb operates logically want to appropriate part of the value created and have some control over this new market. Since this study has shown that private rooms have a greater impact on hotel revenues, the city of Brussels can consider appropriate taxation to balance the market.

The Airbnb housing taxation method can also be adapted to combat the housing crisis in some large cities. Indeed, according to Batirama[14], apartments offered for rent on the Airbnb platform are not available on the traditional long-term rental market. Owners finding it more profitable to rent out their property on Airbnb rather than to locals. There would therefore be a lack of housing for the inhabitants. The authors assume that this is more likely to be the case for entire home/apartments because of the similar characteristics of conventional long-term housing. In order to fight against this housing crisis and to regulate the number of these typical rooms put on the short-term rental market, it would therefore be interesting to tax them more than private rooms. Thus, the gain for owners of this type of room compared to the classic rental of their property would be less. They would therefore envisage more traditional long-term rentals.

By differentiating Airbnb supply by its type of room, authors have found private rooms are more likely to be substitute with hotel rooms in Brussels. This information could be valuable for future hotel openings. Indeed, hotel managers will be in a better position to decide on the location of future hotels. They could avoid regions with a higher private rooms penetration rate in Airbnb supply. By choosing regions with high private rooms penetration rate as location for a new hotel, hotels will be faced to higher competition from Airbnb. Authors have proven regions with higher entire home penetration rate in Airbnb supply are profitable for hotels by an increase of their financial situation. By identifying private rooms as substitute for hotel rooms, authors have added a new valuable information in managers' decision making about the location of new hotels in Brussels.

Among Airbnb hosts, some own several Airbnb accommodations and invest a lot in this short-term rental accommodation type. By knowing private rooms are concurrent with hotel

[14] `https://www.batirama.com/article/24724-la-crise-du-logement-accentuee-par-le-phenomene-airbnb.html`

rooms, they could review their personal investments in order to avoid competition with hotels by choosing entire home or apartment type for their future accommodations.

This last involvment is an assumption of the authors. It takes into account the context in force on 4 June 2020 resulting from the Coronavirus health crisis :

The Covid-19 crisis in the spring of 2020 is having a huge economic impact on the tourism sector in all parts of the world. Airbnb is not necessarily spared. The firm estimates that its turnover in 2020 will be halved compared to 2019[15]. However, Brian Chesky, the CEO of Airbnb is not worried and even indicates that "Airbnb's business will recover completely"[16]. According to the director of Apartur, a tourist agency in Barcelona, "the tourist apartment will adapt more easily to the new times that are coming, to the new needs of tourists, especially in terms of security"[15]. Indeed, the consumer's need for health safety is becoming more and more important. The classic hotel sector involves a certain promiscuity of travellers with the presence of common areas such as restaurants, swimming pools, gyms, receptions, etc. As a result of this crisis, travellers will increasingly want to be independent and isolated from others, so they will increasingly turn to renting entire accommodations in order to guarantee a feeling of distance and therefore security. In a press release of April 2020, Airbnb announced that it would reinforce hygiene measures in order to reassure customers. They announce that homeowners will be trained in cleaning and disinfection[17]. The authors therefore assume that this need for consumer isolation will lead to an increase in demand for entire home/apartments that can guarantee this social distancing, as opposed to private rooms and shared rooms, which imply the sharing of common spaces.

5.3 Personal competences developed during this thesis

For this section, please see annexe A page 41.

5.4 Limits

The geographical segmentation The way authors used for the analysis could be reviewed. Indeed, the authors based their study on a segmentation into neighbourhoods for the Brussels Capital Region. This segmentation is certainly based on the geographical limits set by topographical elements in Brussels such as roads, parks, canals, etc. It was set up to study the demographic data of Brussels in a statistical manner.

In order to study the impact of Airbnb on hotels, a segmentation around the latter would have been interesting. The study would therefore only have taken into consideration Airbnb located within a certain distance of a hotel. A weighting of the impact of an accommodation on a hotel would therefore have been possible on the basis of the distance between them. This notion of distance is more interesting than the notion of neighbourhoods that we have discussed here.

Data availability One of our major limits within this study is the data availability. Indeed, for confidentiality reasons, hotels don't publish or give financial data. MKG Consulting provides some financial hotel data to the authors, but these data are averaged per zone or per number of stars. For future research, it would be useful to test on individual hotels RevPar. We had to limit Airbnb data to be consistent with the hotel data. Time period in our study is monthly but

[15] https://www.rtbf.be/tendance/voyage/detail_avec-le-coronavirus-le-modele-airbnb-prend-une-claque?id=10499156

[16] https://www.airbnb.fr/resources/hosting-homes/t/coronavirus-updates-34

[17] https://www.rtbf.be/tendance/voyage/detail_airbnb-renforce-ses-regles-d-hygiene-pour-rassurer-ses-clients?id=10490747

it concerns only 20 occurrences from May 2018 to December 2019 while Airbnb has been present on Belgian territory for many years. Hotels coming from MKG Consulting data are averages from 86 hotels but only 66 hotels were present inside Brussels. That represents around a third of the total offer of hotels in Brussels.

Construction of variables The construction of the occupancy rate is a limit. We applied a model found by (Department, Amendments in short-term rentals, 2015) for the city of Brussels but this construction has not been validated by economists in researching the impact of Airbnb on the hotel business. We had to put some assumptions for this construction as the average length to stay. If the city concerned (Brussels) doesn't dispose of public statement about Airbnb average length to stay within the city, authors need to take as average length to stay an average (3 nights) for the city, which is the case for the city of Brussels. Authors needed to put another assumption concerning the review rate.

The calculation of the RevPar is defined by multiplying the average price per night and the occupancy rate. However, there is still uncertainty about these two parameters. On one hand, the occupancy rate is based on the number of reviews per month. It takes into account the average length of stay of the occupants and the average propensity to leave a review. These two parameters can vary from one Airbnb to another but generally speaking, it is possible with this to estimate the average occupancy rate for a set of accommodations. On the other hand, the price is an indicative value of the amount paid per night for the occupants. However, this can vary due to various additional charges. There may be extra charges for cleaning (this is the case for 71% of the Airbnb studied, with an average amount of 27.5 €) and charges per additional occupant (this is allowed in 56% of cases for an average amount of 16 €). The price considered in this study therefore does not reflect the real cost of accommodation for guests.

Because of these variations in the possible amount and the approximation of the occupancy rate, the calculation of the RevPar for the Airbnb can be imprecise. The authors have chosen not to take these elements into consideration.

The construction of dependent variables has been made by MKG Consulting for the city in Brussels on a geographical segmentation asked by visits.brussels, allowing the organisation to create the hotel barometer. These variables are classified through "3 variable sorts": all-, area-, (three-, four- and five-). All dependent variables concern monthly hotel financial averages. The "all-" are hotel financial averages, the "area-" are hotel financial averages but by region, the "three-, four- and five-" are hotel financial averages but by number of stars. These constructions limit authors to test for an increase or a decrease of the Airbnb impact on hotel average RevPar by zone depending on the hotel category level for the reason that there is no dependent variable stratified geographically and by hotel category level in MKG Consulting estimates.

Airbnb is considered as leader in peer-to-peer sharing accommodations but there are other smaller platforms in peer-to-peer sharing accommodations. This study only assesses the impact of Airbnb existence on average hotel RevPar in Brussels but doesn't assess the impact of all peer-to-peer sharing accommodations on average hotel RevPar.

Concerning the extent of our study, the results only reflect impact from Airbnb on average hotel RevPar in Brussels. These results can't be extended to other European or worldwide big cities because of several reasons as the date arrival of Airbnb in the city or environment differences in the city.

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Table of Annexes

A | Personal competences developed during this thesis

A.1 Louis Horé

Concerning my personal skills developed during this study, I point out the fact that Louis and I didn't make the same studies. Indeed, Louis has made engineering study and for my part, I've made economics and econometrics studies. It was the first time I worked with someone who has no background in economics in the course of my studies. It allowed for me to learn working in a different environment. In my future work, this learning could be applied if I must face a situation in which I must work with some people with no economic background. The complementarity during the study is a advantage but also a drawback, it depends on both applicants' profiles. I think it was more a force than an disadvantage. The external communication was enriching. During the database search stage, external communication was necessary to find one or more data in order to build one. It was important to manage the schedule but also to identify the data required, to be sure to have targeted a variable, etc... The database search stage was the toughest stage because most of the answers from our requests were negative. The computer skills were also necessary to conduct this study and I improved them (Excel, Stata). The most satisfying part in this study was the fact to conduct an econometric study from the database search stage to the implications for practitioners.

A.2 Louis Breyne

This work was first carried out in several stages over several months. Data collection was a laborious step. Not knowing who to turn to or whom to contact, we had to be patient, persevering and methodical in order to draw up an inventory of what we had access to to carry out this study. Many e-mails were sent, the vast majority without response. We learned as we went along to review our ambitions and adapt ourselves in order to draw up realistic objectives consistent with what we had at our disposal.

Compiling the databases was also a tedious task. We had to be methodical and rigorous in order to process them using Excel and Stata. Because of the specificity of the constitution of the data in the form of panel data, the use of macros via Visual Basic was necessary. We therefore had to learn this language.

It was also necessary to acquire a certain rigour in the research and cross-referencing of information. This necessity pushed us to constantly continue our research, always looking further and further.

Writing a thesis in pairs is also very rewarding. Collaboration on a work of a certain scope is not always easy, but the combination of each person's strengths allows us to achieve a result that we could not have hoped for alone.

Finally, being interested in a subject that is currently taking up so much space is extremely rewarding. Before starting this thesis, we had no idea how big Airbnb could be, especially in Brussels. The collaborative economy is a new turning point in a multitude of markets, the hotel industry is not necessarily immune to it and was even the driving force behind this new trend. Focusing our work on the city of Brussels is all the more stimulating as we feel we are getting involved locally. The places evoked in this work are places that we know, that we locate, we feel all the more concerned, and this was very motivating.

B | Regression results of interaction terms

B.1 Regression results - Kitchen/Free parking

Table B.1: Regression results - Kitchen/Free parking
Source : Stata

AreaRevPar	Coef.	St.Err.	t-value	p-value	[95%Conf	Interval]	Sig
0b.dKitchen # 0b.dFreeParking	0.000	.	.	.	.	.	
0b.dKitchen# 1.dFreeParking	1.441	0.461	3.12	0.002	0.537	2.346	***
1.dKitchen# 0b.dFreeParking	0.302	0.390	0.77	0.439	-0.463	1.067	
1.dKitchen# 1.dFreeParking	1.058	0.472	2.24	0.025	0.133	1.984	**
mdKitchen	-0.401	0.408	-0.98	0.325	-1.200	0.398	
mdFreeParking	0.507	0.307	1.65	0.099	-0.096	1.109	*
mdPetAllowedX mdFreeParking	0.034	0.288	0.12	0.907	-0.531	0.598	
AirbnbSupply	0.040	0.000	266.12	0.000	0.040	0.041	***
OccRateAirbnb	-0.215	0.043	-4.98	0.000	-0.300	-0.130	***
Price	-0.002	0.001	-3.28	0.001	-0.003	-0.001	***
dPrivateRoom	0.344	0.076	4.54	0.000	0.196	0.492	***
ReviewScores	-0.003	0.003	-0.86	0.390	-0.009	0.004	
SecurityDeposit	0.000	0.000	0.40	0.687	0.000	0.000	
dPetAllowed	-0.231	0.108	-2.15	0.032	-0.442	-0.020	**
dOutdoorSpace	0.498	0.153	3.26	0.001	0.199	0.797	***
d24hourCheck	-0.153	0.089	-1.71	0.087	-0.328	0.022	*
dWheelchairAccess	0.004	0.063	0.06	0.955	-0.120	0.128	
dLuggageDropoff	-0.140	0.072	-1.95	0.051	-0.280	0.001	*
dSmoking	-0.106	0.091	-1.17	0.243	-0.284	0.072	
dPrivateEntrance	0.137	0.073	1.87	0.062	-0.007	0.281	*
dGym	0.336	0.249	1.35	0.178	-0.153	0.825	
dPool	0.406	0.813	0.50	0.618	-1.188	2.000	
NightLeisureMonth	0.000	0.000	-265.58	0.000	0.000	0.000	***
NightMeetingMonth	0.000	0.000	148.90	0.000	0.000	0.000	***
y201804	7.716	0.136	56.63	0.000	7.449	7.984	***
y201805	-7.058	0.130	-54.50	0.000	-7.312	-6.804	***
y201807	-0.388	0.125	-3.10	0.002	-0.633	-0.143	***
y201808	8.095	0.147	55.01	0.000	7.806	8.383	***
y201809	-14.529	0.135	-107.92	0.000	-14.793	-14.265	***
y201810	-0.527	0.124	-4.24	0.000	-0.771	-0.283	***
y201811	-14.083	0.127	-110.65	0.000	-14.332	-13.833	***
y201812	-0.232	0.115	-2.01	0.044	-0.458	-0.006	**
y201901	-47.455	0.301	-157.74	0.000	-48.045	-46.865	***
y201902	-38.736	0.252	-153.89	0.000	-39.229	-38.242	***

Table B.1: Regression results - Kitchen/Free parking
Source : Stata

AreaRevPar	Coef.	St.Err.	t-value	p-value	[95%Conf	Interval]	Sig
y201903	-20.952	0.140	-149.70	0.000	-21.227	-20.678	***
y201904	-9.084	0.116	-78.41	0.000	-9.311	-8.857	***
y201905	-2.528	0.109	-23.14	0.000	-2.742	-2.314	***
y201906	-2.207	0.117	-18.87	0.000	-2.436	-1.978	***
Constant	116.636	1.162	100.38	0.000	114.358	118.913	***

Mean dependent var	97.704	SD dependent var	21.007
Overall R-squared	0.935	Number of obs	54.512.000
Chi-square	764.479.934	Prob>chi2	0.000
R-squared within	0.931	R-squared between	0.944

****p<0.01,**p<0.05,*p<0.1*

B.2 Regression results – PetAllowed/Free Parking

Table B.2: Regression results – PetAllowed/Free Parking
Source : Stata

AreaRevPar	Coef.	St.Err.	t-value	p-value	[95%Conf	Interval]	Sig
0b.dPetAllowed# 0b.FreeParking	0.000	.	.	.	.	.	
0b.dPetAllowed# 1.dFreeParking	0.834	0.301	2.77	0.006	0.243	1.425	***
1.dPetAllowed# 0b.dFreeParking	-0.029	0.423	-0.07	0.946	-0.858	0.800	
1.dPetAllowed# 1.dFreeParking	0.574	0.652	0.88	0.378	-0.704	1.853	
mdPetAllowed	-0.215	0.437	-0.49	0.622	-1.071	0.641	
mdFreeParking	0.464	0.323	1.44	0.151	-0.170	1.097	
mdPetAllowedX mdFreeParking	0.315	0.713	0.44	0.658	-1.082	1.713	
AirbnbSupply	0.040	0.000	266.25	0.000	0.040	0.041	***
OccRateAirbnb	-0.216	0.043	-5.00	0.000	-0.301	-0.131	***
Price	-0.002	0.001	-3.23	0.001	-0.003	-0.001	***
dPrivateRoom	0.352	0.075	4.67	0.000	0.205	0.500	***
ReviewScores	-0.003	0.003	-0.87	0.384	-0.009	0.004	
SecurityDeposit	0.000	0.000	0.37	0.709	0.000	0.000	
dKitchen	-0.130	0.124	-1.05	0.295	-0.374	0.113	
dOutdoorSpace	0.499	0.153	3.27	0.001	0.200	0.798	***
d24hourCheck	-0.150	0.089	-1.68	0.094	-0.325	0.025	*
dWheelchairAccess	0.001	0.063	0.01	0.990	-0.123	0.125	
dLuggageDropoff	-0.138	0.072	-1.93	0.054	-0.278	0.002	*
dSmoking	-0.105	0.091	-1.16	0.247	-0.283	0.073	
dPrivateEntrance	0.140	0.073	1.91	0.056	-0.003	0.284	*
dGym	0.363	0.249	1.46	0.145	-0.125	0.851	
dPool	0.324	0.812	0.40	0.690	-1.268	1.916	
NightLeisureMonth	0.000	0.000	-265.57	0.000	0.000	0.000	***
NightMeetingMonth	0.000	0.000	148.91	0.000	0.000	0.000	***
y201804	7.717	0.136	56.64	0.000	7.450	7.984	***
y201805	-7.058	0.130	-54.50	0.000	-7.312	-6.804	***
y201807	-0.387	0.125	-3.10	0.002	-0.632	-0.142	***
y201808	8.094	0.147	55.00	0.000	7.806	8.383	***
y201809	-14.528	0.135	-107.93	0.000	-14.792	-14.264	***
y201810	-0.527	0.124	-4.24	0.000	-0.771	-0.283	***
y201811	-14.080	0.127	-110.65	0.000	-14.330	-13.831	***
y201812	-0.230	0.115	-2.00	0.046	-0.456	-0.004	**

Table B.2: Regression results – PetAllowed/Free Parking
Source : Stata

AreaRevPar	Coef.	St.Err.	t-value	p-value	[95%Conf	Interval]	Sig
y201901	-47.448	0.301	-157.73	0.000	-48.038	-46.859	***
y201902	-38.730	0.252	-153.89	0.000	-39.223	-38.237	***
y201903	-20.949	0.140	-149.69	0.000	-21.223	-20.675	***
y201904	-9.083	0.116	-78.41	0.000	-9.310	-8.856	***
y201905	-2.526	0.109	-23.13	0.000	-2.740	-2.312	***
y201906	-2.204	0.117	-18.85	0.000	-2.434	-1.975	***
Constant	116.653	1.160	100.53	0.000	114.379	118.927	***

Mean dependent var	97.704	SD dependent var	21.007
Overall R-squared	0.935	Number of obs	54.512.000
Chi-square	764.428.321	Prob>chi2	0.000
R-squared within	0.931	R-squared between	0.944

****p<0.01,**p<0.05,*p<0.1*

B.3 Regression results - PriceAirbnb/OccRateAirbnb

As descibed in the hypothesis 4, the interaction term between Airbnb price and occupancy rate is considerd as the RevPar of the Airbnb.

Table B.3: Regression results - PriceAirbnb/OccRateAirbnb
Source : Stata

AreaRevPar	Coef.	St.Err.	t-value	p-value	[95%Conf	Interval]	Sig
Price	-0.005	0.002	-3.15	0.002	-0.008	-0.002	***
OccRateAirbnb	-0.304	0.198	-1.53	0.125	-0.692	0.085	
c.Price# c.OccRateAirbnb	0.005	0.003	1.97	0.048	0.000	0.010	**
mPrice	0.004	0.002	2.00	0.045	0.000	0.007	**
mOccRateAirbnb	-0.209	0.231	-0.91	0.364	-0.662	0.243	
mPriceX mOccRateAirbnb	-0.006	0.003	-1.89	0.058	-0.011	0.000	*
AirbnbSupply	0.040	0.000	267.88	0.000	0.040	0.041	***
dPrivateRoom	0.347	0.075	4.61	0.000	0.200	0.495	***
ReviewScores	-0.001	0.003	-0.36	0.722	-0.008	0.005	
SecurityDeposit	0.000	0.000	-0.33	0.743	0.000	0.000	
dKitchen	-0.174	0.124	-1.40	0.160	-0.418	0.069	
dPetAllowed	-0.227	0.099	-2.30	0.022	-0.420	-0.033	**
dFreeParking	1.260	0.096	13.11	0.000	1.071	1.448	***
dOutdoorSpace	0.511	0.152	3.37	0.001	0.214	0.809	***
d24hourCheck	-0.144	0.089	-1.63	0.104	-0.318	0.030	
dWheelchairAccess	-0.009	0.063	-0.14	0.888	-0.132	0.114	
dLuggageDropoff	-0.106	0.071	-1.48	0.138	-0.246	0.034	
dSmoking	-0.115	0.090	-1.28	0.201	-0.292	0.061	
dPrivateEntrance	0.155	0.073	2.13	0.033	0.012	0.298	**
dGym	0.332	0.247	1.34	0.179	-0.153	0.817	
dPool	0.355	0.789	0.45	0.653	-1.193	1.902	
NightLeisureMonth	0.000	0.000	-265.60	0.000	0.000	0.000	***
NightMeetingMonth	0.000	0.000	148.91	0.000	0.000	0.000	***
y201804	7.708	0.136	56.57	0.000	7.441	7.975	***
y201805	-7.083	0.130	-54.67	0.000	-7.337	-6.829	***
y201807	-0.394	0.125	-3.15	0.002	-0.639	-0.149	***
y201808	8.089	0.147	54.97	0.000	7.801	8.378	***
y201809	-14.538	0.135	-108.01	0.000	-14.802	-14.275	***
y201810	-0.540	0.124	-4.34	0.000	-0.784	-0.296	***
y201811	-14.092	0.127	-110.71	0.000	-14.341	-13.842	***

Table B.3: Regression results - PriceAirbnb/OccRateAirbnb
Source : Stata

AreaRevPar	Coef.	St.Err.	t-value	p-value	[95%Conf	Interval]	Sig
y201812	-0.240	0.115	-2.08	0.037	-0.466	-0.014	**
y201901	-47.460	0.301	-157.76	0.000	-48.050	-46.870	***
y201902	-38.737	0.252	-153.91	0.000	-39.230	-38.244	***
y201903	-20.951	0.140	-149.69	0.000	-21.225	-20.677	***
y201904	-9.085	0.116	-78.40	0.000	-9.312	-8.858	***
y201905	-2.531	0.109	-23.17	0.000	-2.745	-2.317	***
y201906	-2.206	0.117	-18.86	0.000	-2.435	-1.977	***
Constant	116.683	1.161	100.53	0.000	114.408	118.958	***

Mean dependent var	97.704	SD dependent var	21.007
Overall R-squared	0.935	Number of obs	54.512.000
Chi-square	765.519.484	Prob>chi2	0.000
R-squared within	0.931	R-squared between	0.945

****p<0.01,**p<0.05,*p<0.1*

B.4 Regression results - PrivateRoom/PenetrationRate

Table B.4: Regression results - PrivateRoom/PenetrationRate
Source : Stata

AreaAvPrice	Coef.	St.Err.	t-value	p-value	[95%Conf	Interval]	Sig
0b.dPrivateRoom	0.000	.	.	.	.	.	
1.dPrivateRoom	72.431	1.765	41.05	0.000	68.973	75.890	***
PenetrationRate	77.431	1.817	42.61	0.000	73.869	80.993	***
0b.dPrivateRoom# c.PenetrationRate	0.000	.	.	.	.	.	
1.dPrivateRoom# c.PenetrationRate	-149.869	4.174	-35.90	0.000	-158.050	-141.687	***
mPenetrationRate	-64.631	2.773	-23.31	0.000	-70.065	-59.197	***
mdPrivateRoom	-51.404	2.616	-19.65	0.000	-56.531	-46.277	***
mPenetrationRateX mPrivateRoom	92.494	6.208	14.90	0.000	80.325	104.662	***
Price	-0.001	0.001	-0.92	0.355	-0.004	0.002	
OccRateAirbnb	-0.058	0.061	-0.95	0.341	-0.177	0.061	
ReviewScores	-0.001	0.008	-0.16	0.872	-0.018	0.015	
SecurityDeposit	0.001	0.000	3.28	0.001	0.000	0.001	***
dKitchen	-0.468	0.355	-1.32	0.187	-1.163	0.227	
dPetAllowed	-0.045	0.346	-0.13	0.897	-0.723	0.633	
dFreeParking	0.883	0.268	3.30	0.001	0.358	1.408	***
dOutdoorSpace	-0.212	0.368	-0.58	0.564	-0.933	0.509	
d24hourCheck	-0.170	0.375	-0.45	0.650	-0.904	0.564	
dWheelchairAccess	-0.690	0.252	-2.73	0.006	-1.184	-0.195	***
dLuggageDropoff	0.268	0.175	1.53	0.125	-0.075	0.611	
dSmoking	-0.621	0.302	-2.06	0.040	-1.212	-0.030	**
dPrivateEntrance	-0.161	0.277	-0.58	0.562	-0.703	0.382	
dGym	0.551	0.743	0.74	0.458	-0.904	2.006	
dPool	8.983	3.204	2.80	0.005	2.703	15.262	***
NightLeisureMonth	0.000	0.000	-235.99	0.000	0.000	0.000	***
NightMeetingMonth	0.000	0.000	107.27	0.000	0.000	0.000	***
y201804	8.382	0.154	54.49	0.000	8.081	8.684	***
y201805	-10.183	0.146	-69.88	0.000	-10.469	-9.898	***
y201807	-8.169	0.139	-58.79	0.000	-8.441	-7.896	***
y201808	-0.884	0.158	-5.59	0.000	-1.194	-0.574	***
y201809	-18.698	0.150	-125.04	0.000	-18.991	-18.405	***

Table B.4: Regression results - PrivateRoom/PenetrationRate
Source : Stata

AreaAvPrice	Coef.	St.Err.	t-value	p-value	[95%Conf	Interval]	Sig
y201810	-4.754	0.139	-34.18	0.000	-5.026	-4.481	***
y201811	-18.417	0.143	-128.48	0.000	-18.698	-18.136	***
y201812	1.113	0.124	8.98	0.000	0.870	1.356	***
y201901	-37.301	0.318	-117.18	0.000	-37.925	-36.677	***
y201902	-36.956	0.267	-138.19	0.000	-37.480	-36.432	***
y201903	-16.971	0.153	-111.00	0.000	-17.271	-16.672	***
y201904	-9.971	0.123	-81.02	0.000	-10.212	-9.729	***
y201905	3.701	0.117	31.50	0.000	3.471	3.931	***
y201906	-3.920	0.124	-31.59	0.000	-4.163	-3.677	***
Constant	180.120	2.100	85.78	0.000	176.004	184.235	***

Mean dependent var	125.831	SD dependent var	21.717
Overall R-squared	0.615	Number of obs	54.512.000
Chi-square	509.822.047	Prob>chi2	0.000
R-squared within	0.912	R-squared between	0.290

****p<0.01,**p<0.05,*p<0.1*

B.5 Regression results - EntireHome/PenetrationRate

Table B.5: Regression results - EntireHome/PenetrationRate
Source : Stata

AreaRevPar	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
0b.dEntireHome	0.000	.	.	.	.	.	
1.dEntireHome	-81.086	1.966	-41.25	0.000	-84.939	-77.234	***
PenetrationRate	-59.946	2.946	-20.35	0.000	-65.721	-54.172	***
0b.dEntireHome# c.PenetrationRate	0.000	.	.	.	.	.	
1.dEntireHome# c.PenetrationRate	151.334	4.013	37.71	0.000	143.469	159.200	***
mPenetrationRate	14.624	3.600	4.06	0.000	7.567	21.681	***
mdEntireHome	20.596	2.428	8.48	0.000	15.837	25.355	***
mPenetrationRateX mEntireHome	-38.112	4.745	-8.03	0.000	-47.412	-28.812	***
Price	0.001	0.001	0.89	0.373	-0.001	0.004	
OccRateAirbnb	-0.028	0.058	-0.48	0.633	-0.141	0.086	
ReviewScores	0.005	0.007	0.72	0.473	-0.009	0.019	
SecurityDeposit	0.001	0.000	2.77	0.006	0.000	0.001	***
dKitchen	-0.361	0.292	-1.24	0.217	-0.934	0.212	
dPetAllowed	-0.275	0.269	-1.02	0.307	-0.801	0.252	
dFreeParking	0.634	0.225	2.81	0.005	0.192	1.076	***
dOutdoorSpace	-0.155	0.321	-0.48	0.630	-0.785	0.475	
d24hourCheck	0.266	0.279	0.95	0.341	-0.282	0.814	
dWheelchairAccess	-0.694	0.186	-3.73	0.000	-1.058	-0.329	***
dLuggageDropoff	0.225	0.153	1.47	0.141	-0.075	0.525	
dSmoking	-0.483	0.238	-2.04	0.042	-0.949	-0.018	**
dPrivateEntrance	-0.092	0.207	-0.44	0.658	-0.498	0.314	
dGym	-0.213	0.612	-0.35	0.728	-1.414	0.987	
dPool	4.211	2.426	1.74	0.083	-0.543	8.966	*
NightLeisureMonth	0.000	0.000	-242.29	0.000	0.000	0.000	***
NightMeetingMonth	0.000	0.000	148.76	0.000	0.000	0.000	***
y201804	4.285	0.149	28.68	0.000	3.992	4.578	***
y201805	-10.473	0.142	-73.76	0.000	-10.751	-10.194	***
y201807	-3.095	0.136	-22.84	0.000	-3.361	-2.830	***
y201808	5.344	0.153	34.92	0.000	5.044	5.644	***

Table B.5: Regression results - EntireHome/PenetrationRate
Source : Stata

AreaRevPar	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
y201809	-15.840	0.146	-108.60	0.000	-16.126	-15.554	***
y201810	-2.995	0.136	-21.97	0.000	-3.262	-2.728	***
y201811	-15.664	0.141	-111.19	0.000	-15.940	-15.388	***
y201812	-3.244	0.120	-26.98	0.000	-3.480	-3.008	***
y201901	-47.902	0.309	-155.21	0.000	-48.506	-47.297	***
y201902	-38.991	0.260	-150.25	0.000	-39.499	-38.482	***
y201903	-21.398	0.149	-143.59	0.000	-21.690	-21.106	***
y201904	-10.942	0.119	-91.64	0.000	-11.176	-10.708	***
y201905	-2.940	0.114	-25.75	0.000	-3.164	-2.716	***
y201906	-1.900	0.120	-15.79	0.000	-2.135	-1.664	***
Constant	147.395	1.479	99.67	0.000	144.496	150.293	***

Mean dependent var	97.704	SD dependent var	21.007
Overall r-squared	0.823	Number of obs	54.512.000
Chi-square	663.641.027	Prob >chi2	0.000
R-squared within	0.930	R-squared between	0.596

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

C | Descriptive variables

C.1 Evolution of the Airbnb supply by area

Date	**05-18**	**06-18**	**07-18**	**08-18**	**09-18**	**10-18**	**11-18**	**12-18**	**01-19**	**02-19**
Quartier Louise	674	697	734	759	744	703	705	728	737	747
Rogier/Botanique	297	304	314	336	343	329	323	344	348	354
Midi - Lemonnier	386	368	387	398	391	394	398	406	406	402
Grand Place	770	758	795	814	787	762	784	785	809	821
Quartier européen	640	656	699	745	739	716	723	731	719	730
Brussels Airport	64	59	68	76	78	76	76	74	80	81

Date	**03-19**	**04-19**	**05-19**	**06-19**	**07-19**	**08-19**	**09-19**	**10-19**	**11-19**	**12-19**
Quartier Louise	752	771	791	811	831	819	799	778	794	823
Rogier/Botanique	369	372	385	397	421	417	412	399	376	378
Midi - Lemonnier	416	416	436	453	471	459	430	462	502	522
Grand Place	829	844	870	932	945	964	922	956	951	1013
Quartier européen	753	757	786	805	851	834	822	830	833	840
Brussels Airport	84	79	85	89	94	97	89	89	94	94

Table C.1: Evolution of the Airbnb supply by area

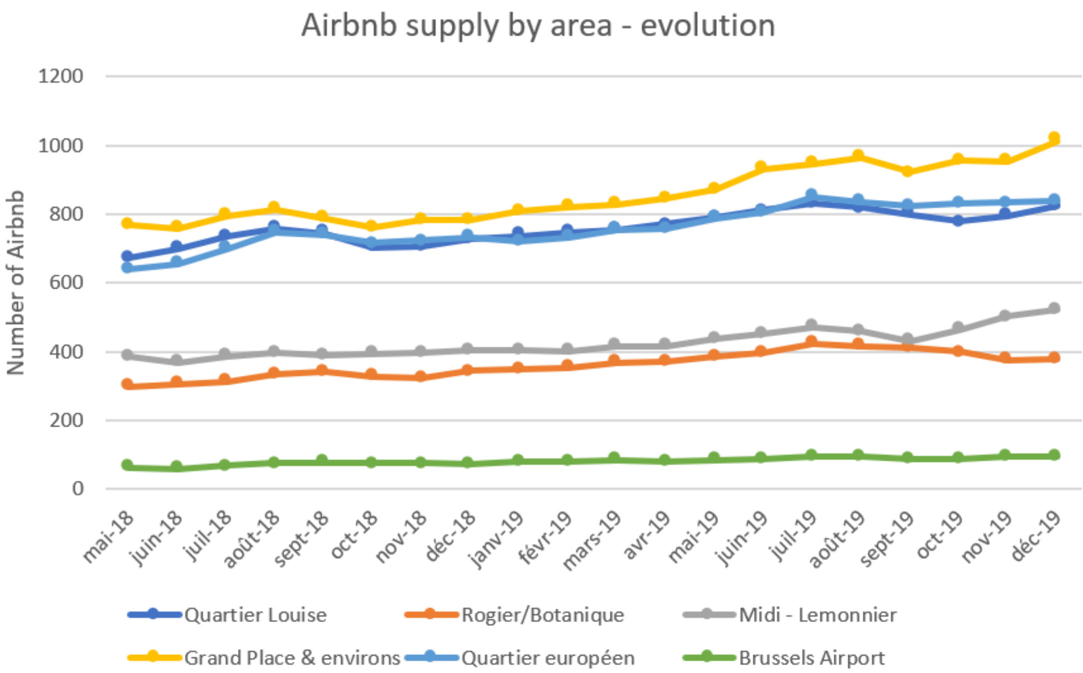

Figure C.1: Evolution of the Airbnb supply by area.

The site l'Echo announces that since 2016, controls have been carried out in Airbnb accommodation. They serve to verify the conformity of the housing in terms of safety, location, health or payment of the appropriate taxes. The actions of the Brussels Economic Inspection have led several guests to remove their rental advertisement. In total, 332 advertisements have been withdrawn in the capital, i.e. almost 5% of the Airbnb accommodation in Brussels[18]. However, the newspaper L'Avenir stated in 2018 that the majority of the capital's housing was not in order[19].

C.2 Evolution of the penetration rate for each room type by area

The penetration rate for a room type is the proportion of this kind of accommodation for a certain area during a period.

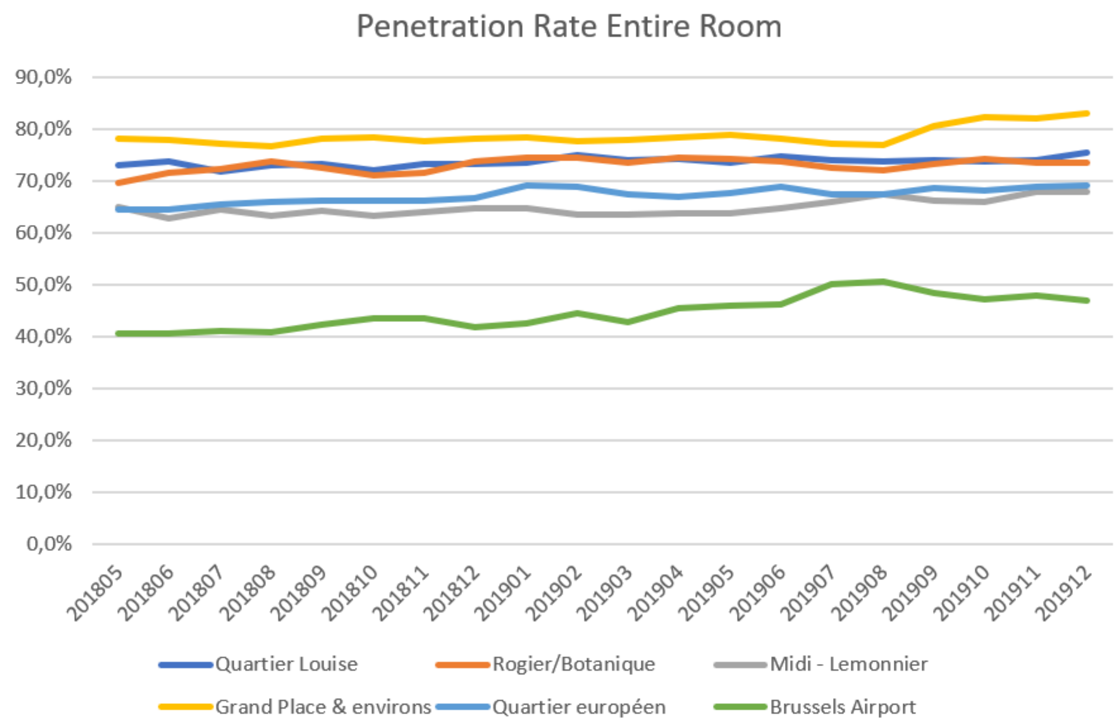

Figure C.2: Evolution of the penetration rate for entire home/apartment

[18]`https://www.lecho.be/monargent/immobilier/rien-n-arrete-la-croissance-d-airbnb-a-bruxelles/10086248.html`

[19]`https://www.lavenir.net/cnt/dmf20180405_01150927/la-majorite-des-7-000-airbnb-bruxellois-n-est-pas-en-ordre`

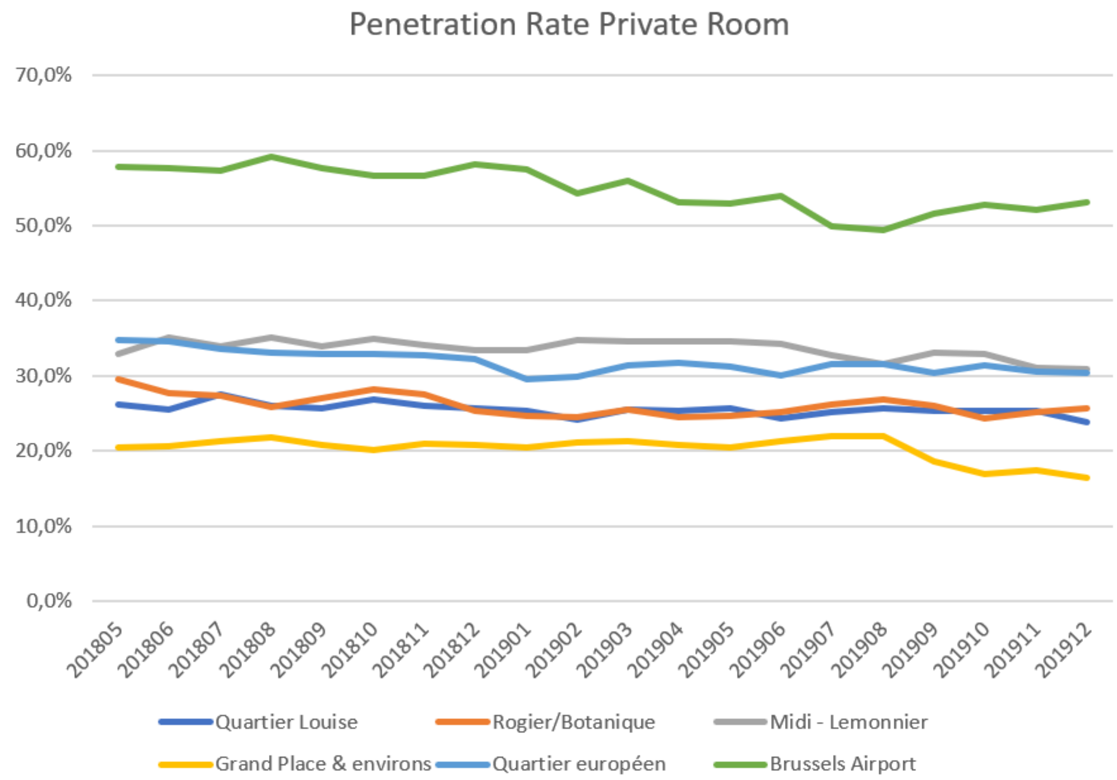

Figure C.3: Evolution of the penetration rate for private room

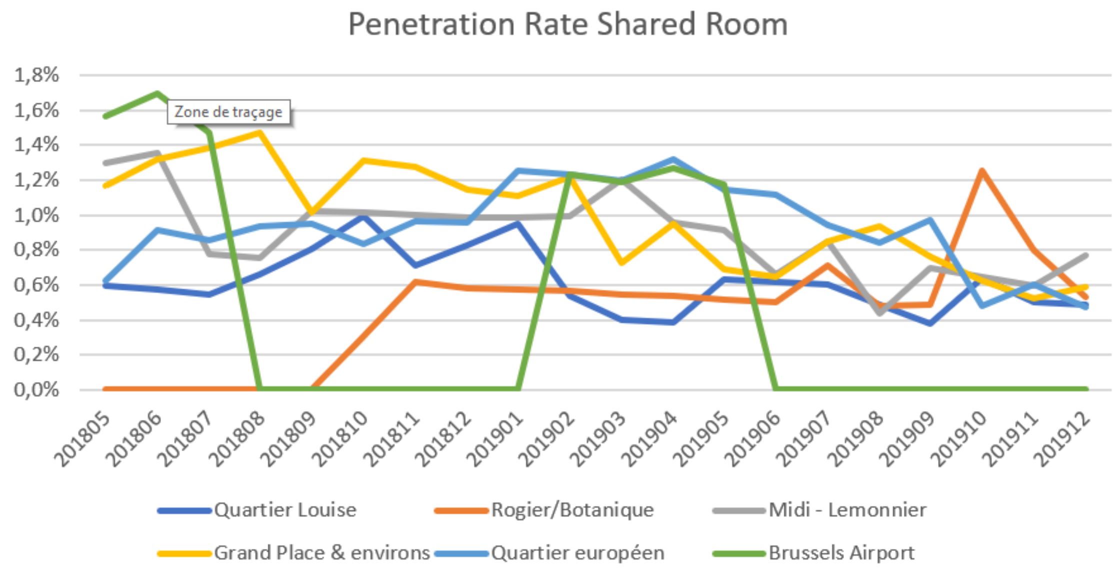

Figure C.4: Evolution of the penetration rate for shared room

C.3 Porportion/number/value of amenities by room type

	Total	Entire Home	Private Room	Shared Room
Total		70.72%	28.42%	0.86%
Beds	1.71	1.91	1.24	1.11
Price	83.44 €	93.88 €	58.07 €	56.08 €
Security Deposit	122.16 €	151.81 €	50.74 €	21.42 €

	Total	Entire Home	Private Room	Shared Room
Kitchen	91.78 %	96.32 %	80.91 %	74.84 %
Pet	10.83 %	10.1 %	12.53 %	15.51 %
Outdoor Space	3.43 %	3.28 %	3.93 %	0 %
WheelChair	35 %	38.2 %	27.32 %	23.67 %
Free Parking	11.1 %	11 %	11.41 %	10.06 %
Luggage Drop Off	17.59 %	19.26 %	13.72 %	6.55 %
Long Term Stay	23.32 %	27.89 %	12.34 %	7.98 %
24h Check	9.21 %	10.35 %	6.52 %	3.77 %
Private Entrance	22.83 %	27.31 %	12.29 %	1.89 %
Smoking Allowed	14.67 %	11.59 %	21.92 %	31.13 %
Gym	1.67 %	1.14 %	2.96 %	3.77 %
Pool	0.21 %	0.18 %	0.28 %	0 %

Table C.2: Source : Inside Airbnb

C.4 Airbnb supply turnover

"Retention rate is the ratio of the number of retained customers to the number at risk". In contractual situations, it makes sense to talk about the number of customers currently under contract and the percentage retained when the contract period runs out[20]. In this case, analysing the incomings and the outgoing in the Airbnb listing each month makes possible to know the turnover of the Airbnb supply.

	05-18	**06-18**	**07-18**	**08-18**	**09-18**	**10-18**	**11-18**	**12-18**	**01-19**	**02-19**
Number of listings	2831	2842	2997	3128	3082	2980	3009	3068	3099	3135
New listings		194	411	323	169	148	195	215	231	171
Deleted listings		183	256	192	215	250	166	156	200	135
	03-19	**04-19**	**05-19**	**06-19**	**07-19**	**08-19**	**09-19**	**10-19**	**11-19**	**12-19**
Number of listings	3203	3239	3353	3487	3613	3590	3474	3514	3550	3670
New listings	204	187	250	271	353	227	269	284	282	264
Deleted listings	136	151	136	137	227	250	385	244	246	144

	05-18	**06-18**	**07-18**	**08-18**	**09-18**	**10-18**	**11-18**	**12-18**	**01-19**	**02-19**
Attrition rate		6,5%	9,0%	6,4%	6,9%	8,1%	5,6%	5,2%	6,5%	4,4%
Rate new listings		6,9%	14,5%	10,8%	5,4%	4,8%	6,5%	7,1%	7,5%	5,5%
Retention rate		93,5%	91,0%	93,6%	93,1%	91,9%	94,4%	94,8%	93,5%	95,6%
	03-19	**04-19**	**05-19**	**06-19**	**07-19**	**08-19**	**09-19**	**10-19**	**11-19**	**12-19**
Attrition rate	4,3%	4,7%	4,2%	4,1%	6,5%	6,9%	10,7%	7,0%	7,0%	4,1%
Rate new listings	6,5%	5,8%	7,7%	8,1%	10,1%	6,3%	7,5%	8,2%	8,0%	7,4%
Retention rate	95,7%	95,3%	95,8%	95,9%	93,5%	93,1%	89,3%	93,0%	93,0%	95,9%

Table C.3: Airbnb supply turnover according to data provided by Inside Airbnb

[20] https://en.wikipedia.org/wiki/Retention_rate

C.5 Hotels financial and statistical data

According to analytics.brussels, there is 190 hotels in Brussels, 129 of these are 1-star, 2-stars or 3-stars, 48 4-stars and 13 5-stars. For comparison, the listing used by the authors count only 66 hotels in brussels, nearly a third.

Brussels hotels recorded some 9.4 million overnight stays in 2019, according to figures from the Visit.Brussels tourist and congress office published on Thursday by Le Soir. The number of overnight stays was still 5 million in 2010 and 8.8 million in 2018. The sector grew by 7% in 2019. According to rtbf.be, Over the year 2019, January was the "lowest" month (with 62% hotel occupancy), while June and October were the best (over 83%)[21]. With our hotel sample, we're getting around the same number.

C.5.1 Evolution by area

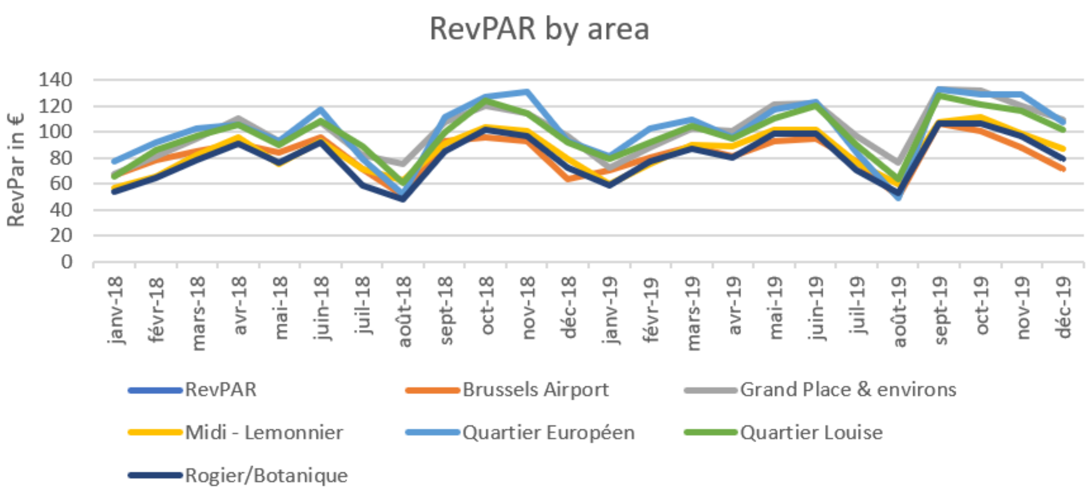

Figure C.5: Evolution of the RevPar of the hotels in Brussels by area

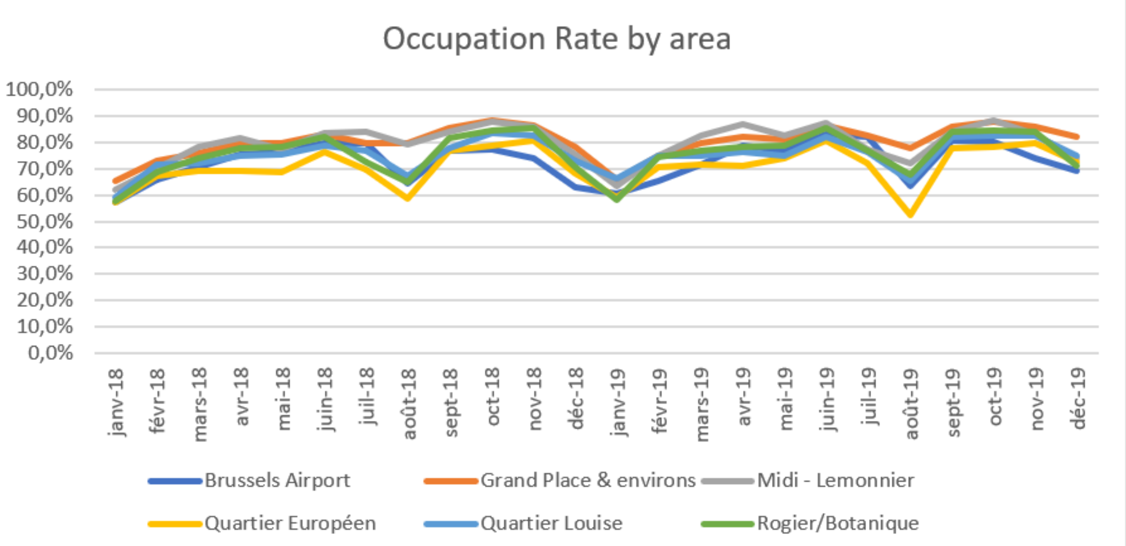

Figure C.6: Evolution of the occupancy rate of the hotels in Brussels by area

[21] https://www.rtbf.be/info/economie/detail_annee-record-pour-le-tourisme-a-bruxelles-avec-quelque-9-4-millions-de-nuitees-enregistrees?id=10395907

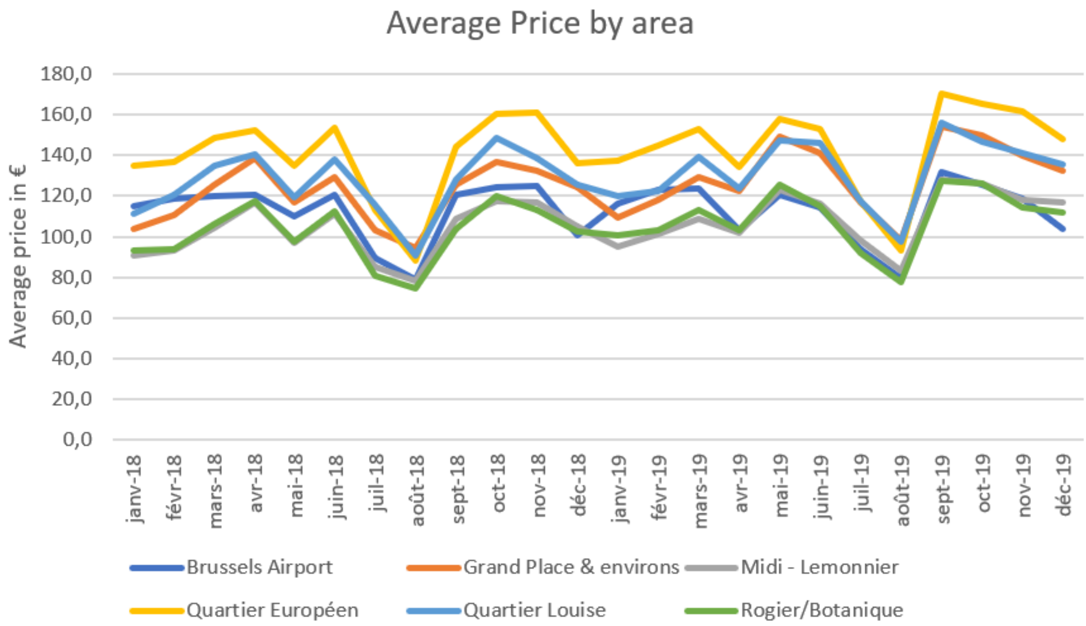

Figure C.7: Evolution of the average price of the hotels in Brussels by area

C.5.2 Evolution by category

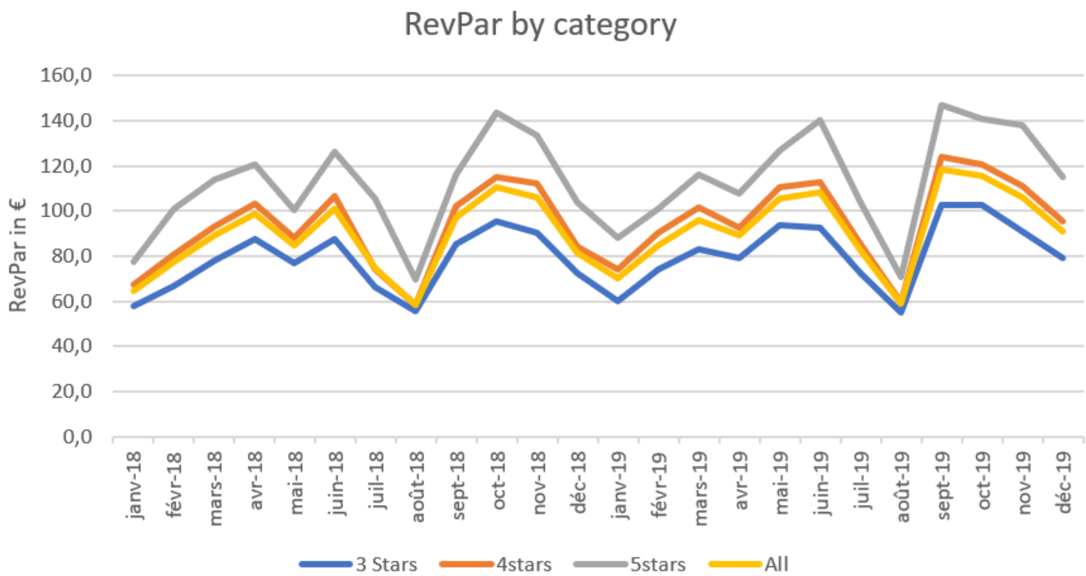

Figure C.8: Evolution of the RevPar of the hotels in Brussels by category

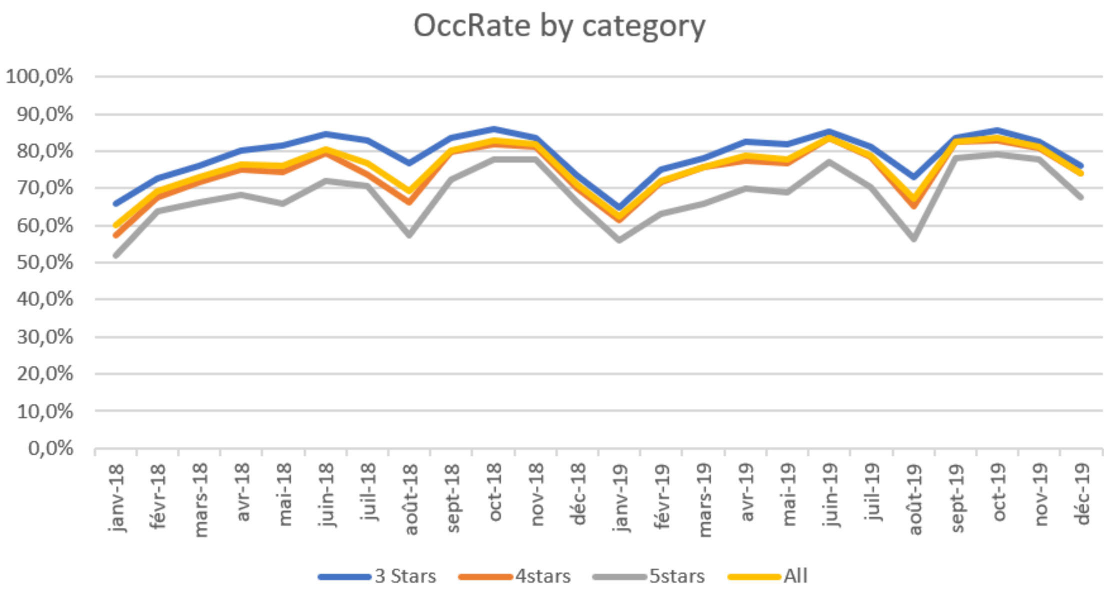

Figure C.9: Evolution of the occupancy rate of the hotels in Brussels by category

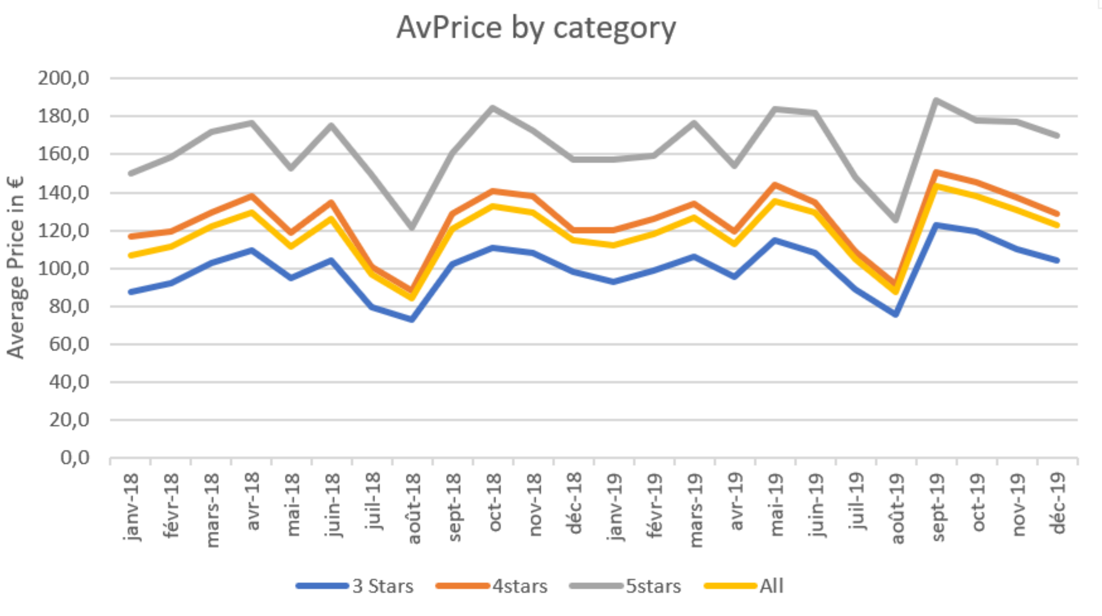

Figure C.10: Evolution of the average price of the hotels in Brussels by category

Created in 2007 and already valued at $31 billion in 2019, Airbnb is a model of profitability worldwide. With the rise of the collaborative economy in recent years, the consumer has appropriated a new way of travelling. More immersive, different from the traditional hotel model and generally cheaper, Airbnb has become in a few years the reference in the way of short-term real estate rental. Airbnb has been able to develop a profitable and competitive business model, but is this new offer to the detriment of the hotel industry in Brussels?
The authors looked at the impact of Airbnb on the hotel market in Brussels from a quantitative perspective. Attention was focused not only on average hotel financial variables in Brussels but also on Airbnb supply diversity on hotel industry competitiveness. Some research have identified Airbnb accommodations and hotel rooms as substitute while others plaid for Airbnb and hotel industry to be complementary. In this econometric study, the case of cohabitation between hotels and Airbnb is analysed in order to define substitution and complementarity trends according to different characteristics related to these different means of short-term accommodation.

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