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The Impact of the Sharing Economy on Residential Prices in Prague

Bachelor thesis

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Abstract

This thesis employs a hedonic regression to measure the impact of Airbnb, the digital platform for short term rentals, on residential prices in Prague. The model is based on the unique transaction dataset of all apartment sales from the first quarter of 2014 to the third quarter of 2018 in Prague. Also, Airbnb listings dataset is used and other datasets containing Prague city data enabling involvement of the property specifications and several neighborhood characteristics influencing the sale price in the model. The main variable of interest included in the regression is Airbnb activity, proxied by the number of Airbnb listings within 300 m of the property at the time of the sale. The results show that a 1% increase in Airbnb activity leads to a 0.0423% increase in sale prices. Moreover, in the city center, the estimated impact is almost twice as high, a 1% increase in Airbnb activity leads to a 0.0816% increase in sale prices. The third hypothesis tested in this thesis shows that the impact of Airbnb has increased in 2017 and 2018. All the estimated results slightly vary, depending on the proxy for Airbnb activity. Nevertheless, estimates in all regressions are statistically significant.

Keywords

Sharing economy, Airbnb, digital platform, hedonic regression, crowd-based capitalism, transaction prices, housing market, regulation

Range of thesis: 72 800 characters with spaces

Abstrakt

Tato práce se zabývá vlivem Airbnb, digitální platformy pro krátkodobý pronájem, na ceny bytů v Praze. Tento jev je zkoumán s využitím hedonické regrese na základě unikátních neveřejných dat o prodejích pražských bytů, které se uskutečnily mezi prvním čtvrtletím roku 2014 a třetím čtvrtletím roku 2018. Dále na základě dat o nabídkách ubytování Airbnb a dalších veřejně dostupných městských dat, která umožňují v modelu zahrnout nejen charakteristiky bytu, ale i charakteristiky okolí, které ovlivňují prodejní ceny residenčních bytů. Hlavní proměnnou v hedonické regresi je aktivita Airbnb, která je vyjádřena počtem bytů, které jsou pronajímány v rámci Airbnb v okruhu 300 m kolem každého prodaného bytu v čase prodeje. Výsledky ukazují, že 1% nárůst v aktivitě Airbnb vede ke zvýšení prodejních cen přibližně o 0,0423 %. V centru města je odhadovaný dopad téměř dvojnásobný, a to 0,0816 %. Poslední hypotézou zkoumanou v této práci je význam vlivu Airbnb na ceny bytů v Praze v čase. Bylo zjištěno, že tento vliv vzrostl v letech 2017 a 2018. Ačkoli se odhadované koeficienty mírně liší v závislosti na zvolené zástupné proměnné pro aktivitu Airbnb, všechny výsledky zůstávají statisticky významné.

Klíčová slova

Sdílená ekonomika, Airbnb, hedonická regrese, crowd-based kapitalismus, transakční ceny, realitní trh, regulace

Declaration of Authorship

1. The author hereby declares that he compiled this thesis independently, using only the listed resources and literature.

2. The author hereby declares that all the sources and literature used have been properly cited.

3. The author hereby declares that the thesis has not been used to obtain a different or the same degree.

Prague, 10 May 2019 **Lucie Schwarzová**

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I would like to express my gratitude to my supervisor PhDr. Michal Hlaváček, Ph.D. for his guidance and Petr Pleticha M.Sc. for his willingness to discuss my questions regarding the researched topic.

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Bachelor's Thesis Proposal

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Notes: Please enter the information from the proposal to the Student Information System (SIS) and submit the proposal signed by yourself and by the supervisor to the Academic Director ("garant") of the undergraduate program.

Proposed Topic:

The impact of the sharing economy on residental prices in Prague

Preliminary scope of work:

Research question and motivation

Sharing economy is a phenomenon which has dramatically risen by now. Unfortunately, there can be more obstacles than benefits if the government will not be able to treat it right way. I will focus on an impact of one of the biggest platform for sharing accommodation Airbnb.

I will analyse the impact of Airbnb platform on apartments prices in Prague, Czech Republic. The main question is if increasing prices of accommodation in Prague are influenced by increasing number of providers of short-term rental services. The aim should be an analysis of this impact in different Prague districts and consequent recommendation of the regulation framework. The other question is if Airbnb is still a sharing economy platform or a "crowd-based" capitalism platform.

In these days there is a big deal with approach to Airbnb (or other platforms) regulation. A magnitude of the influence is not known so far, mostly because there is no regulation yet (i. e. lessor's earnings from this should be considered as an income, thus be a subject to the income tax). Moreover, the more apartments will be used for Airbnb short-term rental, the less apartments will be available for long-term rental which can cause troubles mainly to young people.

Contribution

The outcomes of these analyses should be used as a base for regulatory framework for sharing economy. Also, it should provide the Airbnb impact analysis. There does not exist such study focusing on the correlation among sharing economy and increasing prices of apartments in Prague, although there is a significant discussion about it nowadays.

Methodology

The process will be observed in ten main districts in Prague. I will use data scraped from Airbnb.com and AirDNA.co which contain information about every single offer of short-term accommodation in Prague. These data can be averaged on districts and some time periods, therefore be used as panel data. Also, I will be use scraped data from Sreality.cz web to get information about actual prices of apartments in Prague and thus analyse the connection among these two sets of data.

Outline

1. Introduction
2. Analysis of foreign research
3. Regulation overview
4. Model
   4.1 Data and variables description
   4.2 Panel data analysis
   4.3 Model testing
   4.4 Outcomes evaluation
5. Outcome overview
6. Recommendation of the regulation approach
7. Conclusion

List of academic literature:

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Contents

Introduction

The sharing economy is a phenomenon which has recently seen a dramatic rise. The progress of the sharing economy has been mainly driven by the progress of digital technologies, especially internet access, but also by more profound willingness to share what was once an intensely protected private space.

The subject of this thesis is primarily the sharing of accommodation, specifically the most widespread online platform for accommodation sharing, Airbnb. Although there are many different digital platforms operating on the Prague market with short-term accommodation, such as HomeAway, FlipKey, Vrbo, or House Trip, only Airbnb company is taken into account in this thesis, as it is the most prominent digital platform for short-term rentals in Prague.

Since housing prices on Prague residential market have been increased in recent years, mainly driven by the lack of apartments, the discussion of Airbnb and its regulation has started to resonate on Prague local political scene, as one of the indicators having an impact on increasing residential prices. The crucial aspect in regulatory approach decision-making is to consider the approach based on detailed empirical and data-based analysis (Hospodářská komora České republiky 2018). Since only a few analyses were made on this topic, of which a majority employed non-regression methods, this thesis contributes as a one of the first empirical analysis of the impact of Airbnb on residential prices in Prague.

This thesis aims to empirically estimate the relationship between the number of Airbnb listings and residential prices in Prague. Moreover, I focus separately on the city center, district Prague 1, where the relationship of Airbnb listings and residential prices is presumably higher. Lastly, the time trend of development of Airbnb is examined to determine the significance of this relationship over time, since it is frequently discussed topic on the current political scene. All of these hypotheses are estimated using a hedonic regression approach. Furthermore, in the few analyses that have been performed until now, the impact of Airbnb is not significant. Nevertheless, this thesis employs a different method especially in data processing motivated by Sheppard & Udell (2016) to empirically measure the potential relationship.

The paper by Sheppard & Udell (2016), is the fundamental source for this thesis, offering empirical approach on how to estimate the relationship of Airbnb listings and increasing residential prices. I can employ a similar approach as Sheppard mainly thanks to Společnost pro cenové mapy s. r. o. which provided me with the publicly inaccessible transaction dataset of apartment sales, and thanks to publicly accessible datasets from Prague Institute of Planning and development, data platform Golemio, Otevřené společnosti o. p. s. and other companies and platforms collecting the city data, thereby allowing me to control for different characteristics influencing the sale prices.

The rest of this thesis is organized as follows: Chapter 1 and 2 describe the sharing economy and the situation on the residential market and Airbnb in Prague, Chapter 3 provides a summary of the Czech and foreign analysis of potential impact of Airbnb, Chapter 4 and Chapter 5 describe used datasets, data processing, and methodology and Chapter 6 details the results of the estimation. Finally, Chapter 7 concludes the results of this thesis.

1 Sharing economy

The sharing economy takes many forms based on the goods or service that is the subject of sharing, such as sharing accommodation (Airbnb, Couchsurfing), sharing ride services (Uber, Lyft, BlaBlaCar), bike sharing (Rekola, Freebike, Lime), car sharing (Uniqway, Car4way), boat or plane sharing (WeeShare) or even food (Olio, EatMe) or energy sharing (Green Power Exchange). However, not all of the listed companies are examples of the true sharing economy. Many of these projects, such as Rekola or Car4way, are generally considered as a sharing economy because the main purpose of these project is to share a possession among customers, even though they are more similar to rental companies. Therefore, this chapter focuses on the definition of the true sharing economy, primarily because the definition is the most important and most problematic aspect in setting up a regulatory approach.

1.1 Definition

The sharing economy, also called the collaborative economy, access economy or peer-to-peer economy, is a phenomenon which has recently seen a dramatic rise. Although a single definition of the sharing economy does not exist, mainly because it covers a wide range of sectors, a few definitions are stated here to clarify the idea behind this very frequently used term, either on the political or academic environment or in media.

The term "sharing economy" was added to the Oxford dictionary in 2015 and defined the sharing economy as follows: *"An economic system in which assets or services are shared between private individuals, either free or for a fee, typically by means of the Internet"* (Oxford Dictionaries 2015). The website Investopedia.com defines the sharing economy as *"an economic model often defined as a peer-to-peer (P2P) based activity of acquiring, providing or sharing access to goods and services that are facilitated by a community based on-line platform"* (Investopedia 2019).

As the last example of a definition of "sharing economy" is the definition mentioned in the book "The sharing economy: the end of employment and the rise of crowd-based capitalism" by professor Arun Sundararajan (Sundararajan 2016). Sundararajan points out the eventual misuse of the term "sharing economy" and inclines towards “crowd-based” capitalism, which he finds more precise based on the characteristics of this economic system, rather than “sharing economy.” According to the author, there are five fundamental characteristics of crowd-based economic system: 1) Potential source of higher economic activity due to the development of new services, 2) Newly opened opportunities for assets, skills, time and money to be used as much as possible to their full capacity 3) The supply of labor comes from decentralized crowds rather than centralized institutions 4) Providing services such as a ride or lending money, which was traditionally considered as personal 5) Blurring lines between types of employment and between work and leisure (Sundararajan 2016, p.27).

The other possible term “access economy” comes from the idea that sharing economy is not actually about sharing. Bardhi and Eckhardt (2015) claim that the “sharing economy” relieves the user of the burden of ownership. Thus Access economy seems more accurate for this activity. *“Sharing is a form of social exchange that takes place among people known to each other, without any profit. When “sharing” is market-mediated —when a company is an intermediary between consumers who do not know each other — it is no longer sharing at all”* (Eckhardt & Bardhi 2015).

1.2 Development of the sharing economy

1.2.1 Historical overview

From the historical point of view, the sharing economy is a traditional tool used mainly in times of bad harvest or low productivity of economics. Furthermore, people lived in small trusted communities, thus they were willing to share their possessions. The need for sharing decreased when people moved to cities, thereby small communities became larger which resulted in a higher degree of anonymity in cities. Hence, the trust between people, which is one of the fundamental assumptions of sharing economy, decreased.

Moreover, with the growth of economics and enough consumer goods, the sharing of assets started to seem unnecessary. The idea of sharing economy again boomed after the recession in 2008 and 2009, obviously in order to increase income in the times of high unemployment. The progress of the sharing economy was mainly driven by the progress of digital technologies, especially internet access, which is now widely available even through mobile phones (Marek et al. 2017).

1.2.2 Sharing economy today

As mentioned in the Subsection 1.2.1, the fundamental element of the sharing economy is trust. Trust in the other person, who offer his asset or services. For instance, people get in a car or even share a room with a stranger. Even though people do not live in small trusted communities, there is a highly-developed system of reviews, which substitutes the element of trust in the sharing economy in digital platforms. The customers can read all the reviews that the provider received, and the platforms verify the providers before and after they enter the market. The system of reviews in the sharing economy is a subject of many analyses, for instance, Cheng and Jin (2019), Luo (2018) or Bridges & Vásquez (2017). The latter analyzes the system of reviews on Airbnb.com. They aim to answer the question if the reviews are still meaningful, in case the average rating is 4.7 stars from the maximum of 5[1]. Nevertheless, the rating and reviews and recommendation of guests are essential in the decision-making process for potential customers, and they are essential for the success of hosts (Fradkin et al. 2018).

1.3 Business models of the sharing economy

The sharing economy can be divided according to who or to whom the service or goods are provided (what type of business model is used) or if it is for free or on a commercial basis. The first business model is so-called peer-to-peer (P2P)[2] sharing, also used as an equivalent term for "sharing economy". P2P is described by the following situation: *"Two individuals interact directly with each other, without intermediation by a third-party. Instead, the buyer and the seller transact directly with each other via the P2P service."* (Investopedia 2018). Typical examples of P2P platforms are Uber, Airbnb, BlaBlaCar or Couchsurfing. The digital platform Couchsurfing is different from the rest of the listed companies, mainly because this

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[1] In this analysis, dataset consists of 400 reviews from Airbnb.com, thus this sample size must be taken into consideration when interpreting their results.
[2] This approach is also called C2C (customer-to-customer).

is a platform for literally sharing accommodation without any profit (Řešitelský tým VŠPP 2017, p.35). The other approach is business to customer (B2C) model more typical for traditional businesses. As an example of a B2C model in the sharing economy can be listed DriveNow platform, which is a commercial carsharing service provided and owned by automotive manufacturer BMW (Marek et al. 2017)

2 Situation in Prague

This section is divided into two subsections. The situation on the residential market in Prague will be introduced in the first subsection, while the second section focuses on the Airbnb in Prague since it is the leading digital platform for sharing accommodation in Prague. The second section also provides an overview of the suggested regulation approach of local authorities.

2.1 Residential market in Prague

The residential market in Prague has recently experienced rapid growth both in rental and housing prices. Housing prices have been increasing since 2015 while the economics of the Czech Republic has been strengthening as well. Figure 1, Figure 2, and Figure 3 show the development of housing prices between 2014 and the third quarter of 2018. It is worth noting that these figures are based on data provided by Společnost pro cenové mapy s. r. o., which collected the information about the transactions from the Czech Office for Surveying, Mapping and Cadaster and the local cadastral offices (Cenová mapa prodejních cen 2019). Thus, these figures contain information about prices for m^2 derived from purchase prices, not the supply prices, which are usually higher than purchase prices. For the comparison, two curves are depicted representing prices for m^2 in Prague as a whole and in the city center, district Prague 1, quarterly from the first quarter of the year 2014 until the third quarter of the year 2018. All of the three figures depict the increasing trend in residential prices in Prague. The increase in prices for m^2 in Prague between the first quarter of 2014 and the third quarter of 2018 of apartments in the new buildings is 47%, in the brick houses 62% and in the prefabricated houses even 69%, when the first quarter of 2014 is taken as a base year.

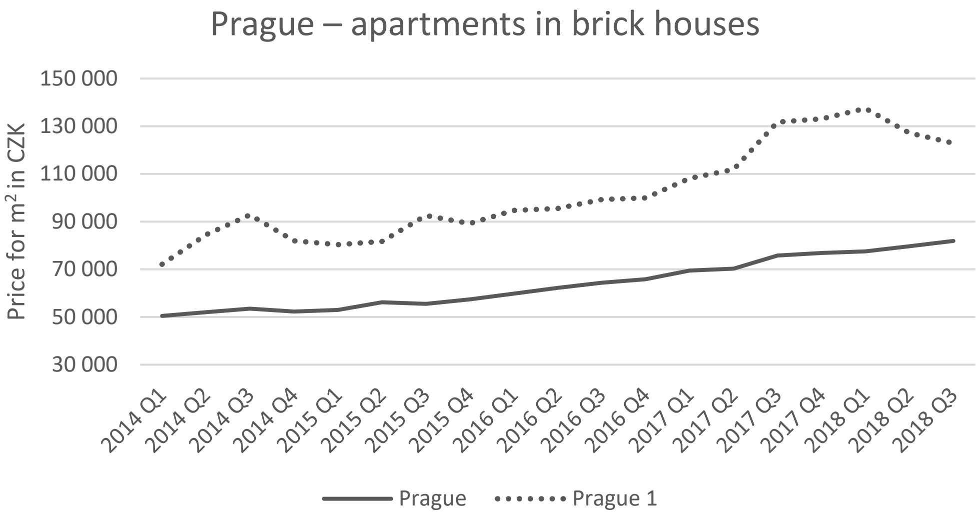

Figure 1 – Development of residential prices for m² in Prague - brick houses

The fluctuation in the increasing trend of prices in district Prague 1 in both Figure 1 and Figure 2 is mainly given by the fact, that the dataset consists transaction only from Prague 1 which comprise rather a small portion of the whole Prague dataset. The fluctuating trend of prices for m² of apartments in new buildings correspond with a very small development in Prague 1, thus, the average quarter price for m² had boosted when new developer project had been finished.

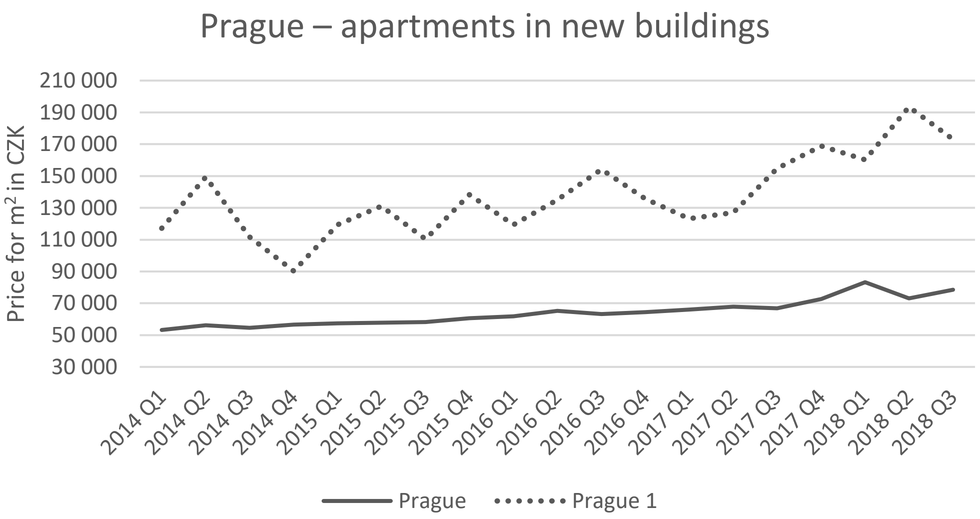

Figure 2 – Development of residential prices for m² in Prague – new buildings

Figure 3 shows a steady increase in prices for m² of apartments in prefabricated houses. Logically, there is no curve for Prague 1 in Figure 3, simply because no prefabricated houses are located in the city center.

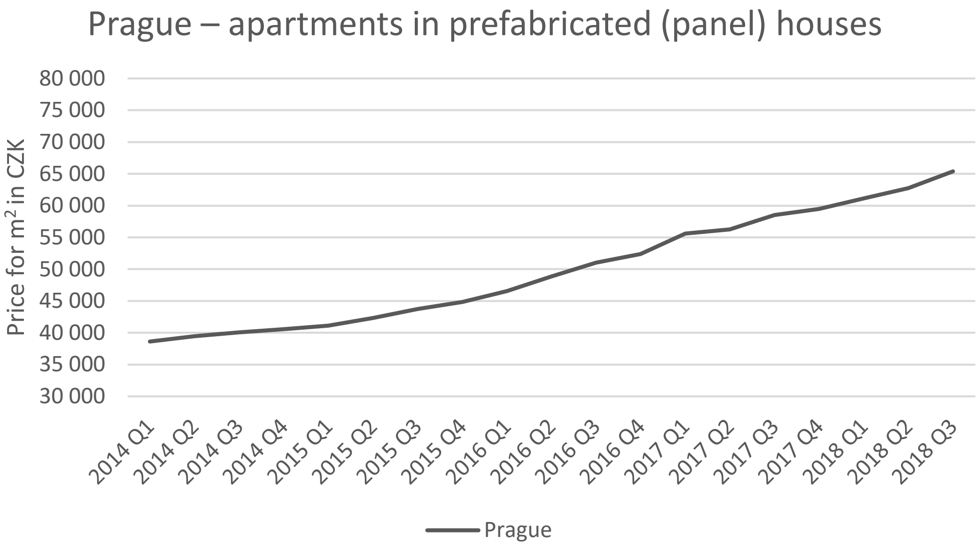

Figure 3 – Development of residential prices for m² in Prague - prefabricated (panel) houses

There are several factors which cause this growth in housing prices. Besides the already mentioned economic boom, associated with the overall increase in prices and income, it is the high demand along with a short supply of apartments in Prague causing the most significant complications. As the fundamental obstacles of short supply of apartments in Prague housing market are considered for instance enormous bureaucracy during the development, the slow speed of development and insufficient Prague local plan (Rod et al. 2018). In the Czech Republic, it takes approximately 246 days to obtain a building permit in case of the minor building (Rod et al. 2018). This placed the Czech Republic on the 127. place out of 156 countries in 2017, and on the 156. place out of 190 countries in 2018 in the project Doing Business, released by the World Bank (Vilímová 2017). The situation in Prague is even worse; the duration of obtaining building permits is on average 1 103 days (Němec 2018). Moreover, the procedure of obtaining permission for a new development project is on average seven years (Rod et al. 2018). Logically, this causes the slowdown of overall development in the capital city. The overall number of supplied apartments and number of new apartments[3] during years 2016 to 2018 are graphically represented in Figure 4 based on the reports from Deloitte company,

[3] As new apartments are considered recently finished apartments, which have not been on the market before. Thus, reconstructed apartments are not included.

which monitors the current situation on the residential market by Develop Index and publishes information about Prague development market (Deloitte 2019). On average, approximately 893 new apartments appear on the market every two months.

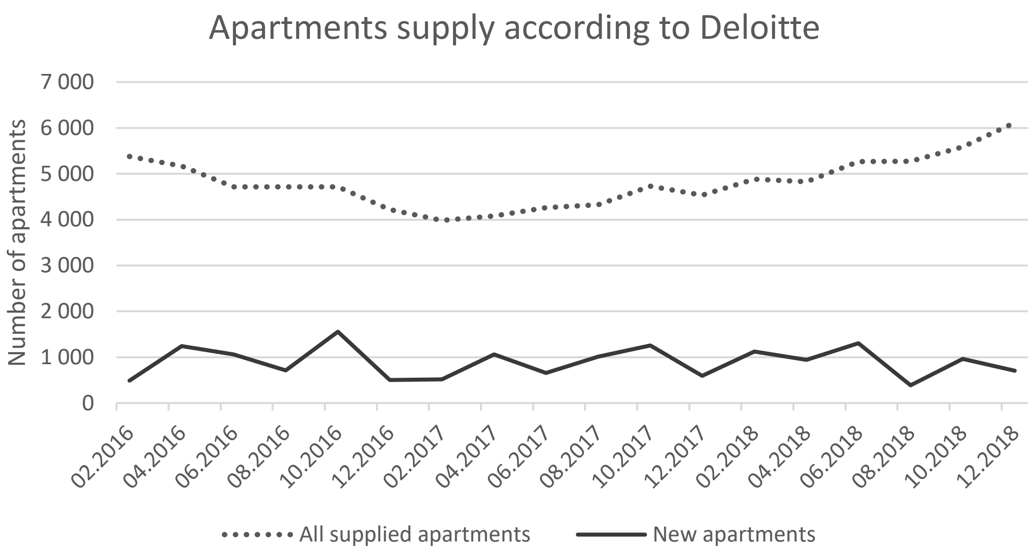

Figure 4 – Supply of apartments in Prague from 2018 to 2018 - Own creation according to Deloitte[4]

Figure 4 indicates that at the end of 2018, there were 6 114 supplied apartments on the market, which is the highest number over the reference period. Unfortunately, the number of new apartments has not significantly risen, and at the end of 2018, there were only 703 new apartments available. The non-increasing trend of the number of new apartments can also be seen in Figure 5 which is based on the analysis of current development projects made by Prague Institute of Planning and Development (Němec 2018). Figure 5 shows the significant decrease in development after the mortgage crisis in 2009[5] and subsequent years. An increment in development has been monitored again during the years 2014 and 2015. The number of new apartments reaches a peak in 2016 with 13 877 new apartments.

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[4] Deloitte reports available at https://www2.deloitte.com/cz/cs/pages/real-estate/articles/cze-develop-index.html

[5] The drop from 2009 to 2010 was from 15 983 to 9 635 new apartments and 149 to 117 developer projects.

However, there is a slight decrease in the number of new apartments in the last few years despite the excess of demand over supply.

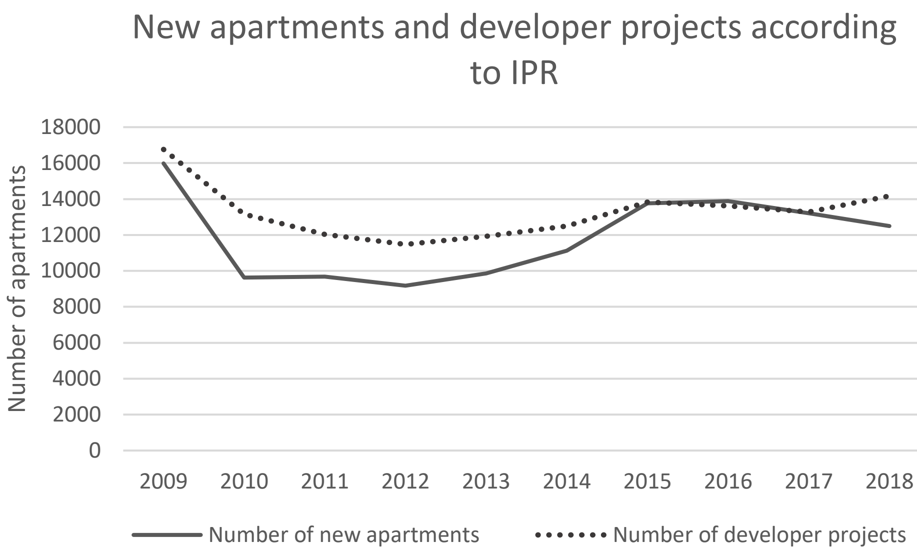

Figure 5 – Number of current developer projects and number of new apartments - Own creation according to IPR[6]

The annual number of new apartments in the analysis by IPR is higher than in the reports by Deloitte because the former also counts the apartments that can be sold in pre-sale, even if the apartments are not on the market yet or the buildings are not finished.

The analysis made by Trigema, Skanska Reality and Central Group, the largest real estate developers in Prague, also highlights that the overall number of sales of apartments decreased by 17% in 2017 due to the short supply of apartments (Central Group 2018).

From the conclusion of the Rod et al. analysis of housing market, partial solution concerning Prague local plan proposes the utilization of so-called “brownfields” (which take approximately 1 400 hectares of Prague area). According to CzechInvest and the Ministry of Industry and Trade of the Czech Republic, *“a brownfield is a*

[6] Based on the analysis available at http://www.iprpraha.cz/uploads/assets/dokumenty/ssp/analyzy/bydleni_realitni_trh/uzemni_analyza_aktualnich_developerskych_projektu_2018.pdf.

property (land plot, building, complex) that is underused or is abandoned and possibly contaminated and cannot be effectively used without undergoing a process of regeneration" (Brownfieldy.eu 2019). Furthermore, according to IPR, there are approximately 300 empty houses in Prague. Reconstructions of these houses are often very expensive, but the fundamental issue of the long procedure is again bureaucracy (ČTK 2017).

The last potential cause is the rise of the sharing economy platforms. Concerning residential market, it is the digital platform Airbnb for short term accommodation which is introduced as one of the potential factors increasing the residential prices (Kliment 2018) and a cause of the outflow of residents from the city center (Marianovská & Němec 2018). On the contrary, the study made by Airbnb based on data from 2017 shows that 55 % of hosts use the income from sharing accommodation to pay a rent or a mortgage, thus the system of sharing economy supports the residents to stay in their current apartments and prevents the outflow of them from the city center (Airbnb 2018).

2.2 Airbnb in Prague

The Airbnb platform has seen rapid growth since its establishment in 2008 and has become a trusted community marketplace offering places to stay in more than 81,000 cities and 191 countries (Airbnb 2018). In Prague, the visitors seeking accommodation have had the opportunity to make use of Airbnb since 2009. Over the last decade, Airbnb has played a significant role in tourism and accommodation in Prague. Last year in Prague in total 12 531 active[7] listings were offered on Airbnb, of which 2 532 were single rooms and 9 717 were whole flats or houses. Predictably, the most preferred location is the city center and the further away from the center, the fewer the number of offers and the lower the prices (Golemio 2018).

Airbnb, as well as other peer-to-peer platforms which enable the direct connection of owners and users and thus enable effective sharing, has a huge impact on current

[7] In this analysis, a listing is considered to be active if after a period of time when the flat was booked the guest made a review.

markets and has become a widely discussed topic, especially in terms of taxes and housing affordability and availability. Many critics, especially residents, argue that due to inefficient regulation in taxes and collection of charges, Airbnb provides a better possibility for property monetization through short-term rental services than through long-term rental services. Thus, many property owners decide to be part of Airbnb or a similar platform and offer rooms of their flats for the use of tourists rather than residents. This results in upward pressure on the prices of residential living due to downward movement in supply. Another issue is that in contrast to regular businesses in the hotel industry, offering flats through Airbnb does not require the fulfillment of many other regulations and standards, such as level of hygiene and security, and this allows more people to join Airbnb.

There are some major questions which arise in discussions about Airbnb. First, as mentioned in Section 1.1, is Airbnb a true example of sharing economy or is it rather a “crowd-based” capitalism platform (Sundararajan 2016)? More widely, how to distinguish between offers in a sharing economy framework and regular business (Bajtler 2018)? How should a regulatory framework be set up and how can these regulations be enforced (Hospodářská komora České republiky 2018)?

Supporting sharing economy systems and better resource utilization seems very important for many cities and governments especially for developing tourism. Approaches to dealing with Airbnb differs from city to city and mainly depend on existing local regulations and the willingness of local authorities to adapt to new technologies. Some local authorities tend to forbid such platforms; some allow only single rooms to be offered, not whole flats; some of them try to collaborate with Airbnb in the collection of charges and taxes, while some local authorities have not yet set up an approach. In the last category, is Prague.

2.3 Regulatory framework

Undoubtedly, the main subject of the current discussion about sharing economy is regulation, which covers all further issues e. g. taxes, economic, legislative, social, etc. Concerning the regulation of the sharing economy, it should be noticed that European Union provides a set of guidance and policy recommendations for sharing economy, therefore there are no strict rules for Member states set by the European

Union (EUROPA - European Commission 2016). The potential approaches of regulation of the sharing economy according to Prague local authorities and current discussions are summarized below.

The issue of Airbnb started to appear on the political scene approximately in 2017 and has been resonating since 2018. The main reason why local authorities have not set any regulatory framework specifically for short term rentals yet, namely Airbnb, is due to the Prague municipal election, which took place in Autumn 2018. To be specific, the former local authorities had not done fundamental changes at the end of their mandate, and new local authorities have not set any yet. On the other hand, the regulatory framework concerning taxes (especially the income tax, paid to the local Tax offices according to the Act No 586/1992 Coll.) and local fees, paid to the municipal district authority according to the Act No. 565/1990 Coll., on Local Fees, is clearly defined. Therefore, the fundamental issues on the Prague political scene are how to enforce the law and how to control that provider of the short term rental stick to the rules and pay taxes and local fee. Therefore, the Czech Chamber of Commerce prepared the recommendation for development of the sharing economy, where they point out the necessity of making detailed analysis of the situation in Prague Airbnb market to consider in which sectors should be the regulations (if any) applied and how to set up an approach to cover the sharing economy in the already existing laws.

Firstly, the sharing economy must be distinguished from regular business. The author suggests to distinguish the sharing economy from the regular business and categorize it in three groups based on the amount of host´s income – occasional income, extra income, and economic activity required a trade license (Hospodářská komora České republiky 2018). Some analyses of Airbnb in Prague point out the fact that the regular business is dominant on Airbnb Prague market, approximately 70% of all listings (Colliers International 2017) or even 80% of all listings available at that time are subject of regular business (Řešitelský tým VŠPP 2017). This information is based on the assumption that all offered entire homes listings are subject of regular business. However, the entire home listings do not necessarily imply that these apartments are offered as a regular business. Another indicator of whether the listing is a subject of business or not is the number of days per year when the listing is booked.

The entire home listings can be considered as the sharing economy if the number of booked days per year does not exceed a determined number of days[8] when the owner can be on vacation or business trip. The regulation, restricting the number of days when the listings are booked, is very frequently applied e. g. in Amsterdam, Paris or Berlin. According to data platform Golemio, approximately 50% of listings in Prague can be considered as a subject of business based on the limit of 60 days booked per year, as suggested by leading political party in Prague[9] (Golemio 2018). The main reason is to make Airbnb less attractive for hosts and make them prefer long-term rent for residents, thereby raising the inflow of apartments on the rental (or residential) market in Prague (Úšela 2018).

Secondly, there is a discussion about the collection of local fees of 15 CZK per day. Currently, hosts should pay this fee to the municipal authority, but there is no mechanism on how to enforce or control if they are actually paid. The solution should be the planned amended Act No. 565/1990 Coll., on Local Fees. It suggests the increase of local fees to 21 CZK per day in 2020, and further increase on 50 CZK per day in 2021 (Žurovec 2018). Moreover, the local fees should be paid by Airbnb instead of hosts to lower the bureaucracy for a host offering the apartment occasionally. As mentioned above, these regulations should motivate hosts to offer apartments to residents rather than provide short term rentals. Even though the discussions mostly cover the regulation of Airbnb, the regulatory framework would involve any digital platforms for short term accommodation operating in Prague.

In conclusion, the regulatory framework should be effectively enforceable and should not lead to the shift of the sharing economy to the shadow economy (Hospodářská komora České republiky 2018).

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[8] The restriction of 120 days per year is applied in Paris, 90 days in Berlin, 60 days in Amsterdam.

[9] The Pirates political party [2018].

3 Literature review

In this section, a few studies concerning the impact of the sharing economy will be presented and shortly summarized. This section is divided into two subsections, the first one deals with studies of the impact of the sharing economy in the Czech Republic, while the second one provides an overview of the foreign studies.

3.1 Analysis of Czech studies

The question of the sharing economy, especially the peer-to-peer platform Airbnb, concerning the Czech Republic have arisen just in a few studies so far. These, which already exist, focus on the impact of home-sharing on the residential market in Prague, the capital of the Czech Republic, where concerns about the potential impact on residential prices are frequently discussed these days.

Marianovská and Němec (2018) analyze the supply of accommodation via Airbnb in Prague. This analysis based on data from AirDNA.co provides many aggregate statistics about the price, occupancy and other crucial aspects of Airbnb accommodation in Prague. Also, this analysis provides a comparison between Prague and other European cities. It focuses on social and economic impacts, especially the negative ones, of such platforms which may cause problems in the housing market, tourism or quality of life of residents in the most frequent places. They aim to determine the magnitude of Airbnb supply in Prague via the capacity of the Prague dwelling fond, and clear rules for using and providing the home-sharing.

Furthermore, the authors emphasize the negative consequences of the increasing interest in the Airbnb platform in Prague, such as noise, which causes problems, especially in the district Prague 1; lower supply of services for residents in the city center and distortion of the long-term rental market. However, Rod et al. (2018) point out the fact that the Airbnb does not operate on the Prague market for such a long time to claim Airbnb might influence the housing prices.

Moreover, the share of the Airbnb accommodation in the overall number of dwellings[10] in Prague is just 1.8% (Rod et al., 2018). Detailed descriptive analysis by Marianovská and Němec (2018) of Airbnb supply in Prague is based on the information from AirDNA.co, which was available on this website during April and May 2018. In comparison with other European cities, in Prague, there is the second lowest share of single hosts (69%)[11], which implies the above-average[12] number of hosts who might be considered as professionals or even entrepreneurs.

Ključnikov et al. (2018) investigate the size of Airbnb sector in Prague and identify a potential scale of tax evasion of the Airbnb hosts to state the need for additional regulation. This data set, obtained by the method of web scraping, consists of 18 586 listings which were offered by 8943 hosts from April 2016 to March 2017. The method of web scraping is widely used to collect Airbnb data by e. g. Sharma (2018) and Barron, Kung and Prosperio (2018). They also point out that 7.4% of hosts control approximately 39.56% of the market, offering 7338 units of accommodation. It is worth noting that Marianovská and Němec (2018) claim that there are many professional hosts or even companies which offer services including photographing the flat, preparing the profile on Airbnb.com and all other necessity, which are related to offering the flat via any of the platforms for offering accommodation (Blahobyty.cz 2019). One of the conclusions suggests that almost 47% of all Airbnb hosts reached the annual average earnings about 12 326 CZK. Thus, there is no need to regulate this market because of such low earnings. On the other hand, the authors suggest that the local authorities should focus on providers who offer their accommodation for more than 30 days per year.

There are further articles and studies related to the analysis of the impact of Airbnb on the housing market in Prague, providing a theoretical perspective of the impact

[10] According to Dolák (2016), the overall number of dwellings in Prague was approximately 610 000 in 2016.
[11] AirDNA.co, May 2018
[12] In comparison with 11 European cities – Krakow, Copenhagen, Munchen, Berlin, Amsterdam, Budapest, Bratislava, Vienna, Warsaw, Barcelona, Milano

on the housing market (Krivošová 2018) and descriptive analysis of the Airbnb magnitude in Prague (Golemio 2018).

3.2 Analysis of foreign studies

Sheppard, & Udell (2016) provide a variety of estimates of the actual impact of Airbnb accommodation on housing prices in New York City using several datasets to cover all the potential effects that might have influenced the sale prices of flats in New York City. It is worth noting that they used the dataset of sale prices contained information about all sales in New York City between 2003 and 2015. The empirical approach based on the model of hedonic regression shows that the increase in the local supply of Airbnb is associated with an increase in property values. They conclude that with a 1% increase in Airbnb activity, the measured impact on the residential prices is between 0.06 and 0.11%. The second approach of using differences-in-differences model is motivated by Zervas & Proserpio, & Byers (2017) who analyze the Airbnb as a competitor to the traditional hotel industry in Texas. Sheppard, & Udell (2016) conclude that the estimated impact results in approximately 31% increase in value for treated properties, meaning those properties which were sold after Airbnb had appeared on the market (2009). Sheppard, & Udell (2016) besides the econometric models, use a simple monocentric urban model to support the theoretical arguments and underline their empirical findings.

Lee (2016) employs non-regression methods to verify the hypothesis that short-term rentals, such as Airbnb, have deepened the affordable housing crisis in Los Angeles. Moreover, he provides some strategy recommendation for municipal policymakers, how to regulate the Airbnb effectively. He agrees that Airbnb distorts the housing market in many ways as well as (Barron et al. 2018). He focuses on two of them. The first one is quite straightforward – the more units appear on the Airbnb website, the fewer units are available for residents. The second one is called "hotelization". In other words, the property owner is more incentivized to offer room below the price of hotel rooms because of the higher profit he or she can make instead of long-term rent to Los Angeles residents. The recommendation of Lee

(2016) consists of days per year limitation when a flat can be listed; otherwise, the author suggests the 14% tax in order to balance the competition with hotels.

Zervas & Proserpio, & Byers, (2017) examine the Airbnb as a competitor to the traditional hotel industry. They analyze the situation in Texas, where the most noticeable impact of Airbnb on hotel revenue is in Austin, using a dataset of Airbnb listings from 2008 to 2014. One of the conclusions suggests that there is a decrease between 8-10% in hotel revenue since Airbnb have entered the market. In contrast, Aznar & Rocafort, & Galiana, (2017) find a positive correlation between the presence of Airbnb and the hotel return of equity. However, based on the differences-in-differences approach with monthly hotel room revenue being the dependent variable, Zervas et al. (2017) show that hotels in areas where Airbnb operates have decreased the prices as a response to increasing competition, which lowers their revenue, but benefits all travelers, no matter if they use Airbnb or not.

A study by Barron & Kung, & Proserpio, (2018) aims to assess the impact of home-sharing on residential prices and rents. Based on the dataset of Airbnb listing from the entire United States, using instrumental variables estimation strategy, they conclude that a 1% increase in Airbnb results in a 0.018% increase in rents and 0.026% increase in house prices.

Further studies have been made on this topic including analysis focus on the regulation of Airbnb (Kaplan, & Nadler, 2015) the impact on hotel industry (Xie, & Kwok, 2017, Blal & Singal, & Templin, 2018) or the pricing in Airbnb (Wang, & Nicolaub, 2017, Gibbs et al, 2017). This thesis is mostly related to the empirical approach of Sheppard, & Udell, 2016, which provides a base for the model and data processing used in this thesis.

4 Data and descriptive statistics

For this analysis, many types of datasets were used in order to capture as many factors as possible which may have influenced the sale price of the apartment. All datasets used in this analysis are shortly summarized in the table below. Furthermore, a detailed description of the essential datasets, data collection, and measurement procedure are provided in this chapter.

Name & Source	Description & Use
Transaction dataset, Společnost pro Cenové mapy s. r. o.	The dataset contains information about all apartment sales between 2014 and the third quarters of 2018 in Prague. It contains variables such as sale price, floor area, GPS coordinates, date of a transaction, etc.
Airbnb listings, Data Platform Golemio	Dataset provided by Mgr. Adam Nedvěd from Blahobyty.cz contains information about all Airbnb listings in Prague e. g. room ID, date of the first review, number of bedrooms, GPS coordinates, etc. and also nightly price and occupancy rate.
Crime index, Mapakriminality.cz	Crime index from mapakriminality.cz is provided by Police of the Czech Republic and uploaded on mapakriminiality.cz by Otevřená společnost, o.p.s.
Prague public transport stops, Opendata.praha.eu	Public stops data in javascript format are provided by ROPID, it contains GPS coordinates of all public transport stops (bus, tram, metro).
Prague Parks, Opendata.praha.eu	Prague Park data in javascript format are provided by Operátor ICT, a. s., contains GPS coordinates that define the area of the biggest parks in Prague, such as Stromovka, Letná, Petřín, etc.
Prague Noise Map, Opendata.praha.eu	Noise map in Shapefile format processed by EKOLA group, spol. s. r.o. for IPR contains noise zone at night (that is 22:00 – 06:00), per 5 dB in the height of 4 m.

Table 1 - Data description

4.1 Transaction dataset

Dataset provided by Společnost pro Cenové mapy s. r. o. contains information about 67 680 completed sale transactions of apartments in Prague. The data in the Transaction Price map comes from the Czech Office for Surveying, Mapping and

Cadaster and the local cadastral offices (Cenová mapa prodejních cen 2019). I want to point out the uniqueness of this dataset containing the information about every single sale of an apartment between the first quarter of 2014 and the third quarter of 2018. Furthermore, this dataset is not publicly accessible, and it was provided for the purpose of making a consistent analysis of Airbnb phenomenon in Prague.

Data about non-standard sales transaction such as the sale of apartments in privatization from cities or municipal boroughs, transfers of shares in a cooperative, etc. are excluded from the dataset (Cenová mapa prodejních cen 2019). Thus, this dataset contains the exact information about all standard sales of apartments needed for this type of analysis.

4.2 Airbnb dataset

4.2.1 General information

Airbnb dataset provided by Mgr. Adam Nedvěd from Blahobyty.cz and Prague Data Platform Golemio from the municipal enterprise Operátor ICT, a. s., has been scraped from the Airbnb.com website. The data have been scraped on a daily basis since 2016, with a pause for a few months in 2017, when Airbnb changed the algorithm on the website. Thus, the limitation of this dataset without listings that exited the market before 2016 must be taken into consideration. The data provided for this thesis are aggregated to the database with all the listings, that were offered on the Airbnb website from March 2016 to January 2019. Thus, the information about variables in this dataset was last updated in January 2019. The other dataset is a panel with occupancy and prices that have been detected in the calendar on each listing´s webpage. The prices in the dataset are computed as the average of prices from the booked stays (according to the calendar) in the particular month. This dataset was used just for descriptive analysis. However, it is worth noting that I have to consider some essential limitations connected with the system of how Airbnb website works.

Firstly, it is possible for hosts to book one day before and one day after each stay to clean and prepare the apartment for another stay. Thus, the calendar scraped by the robot seems always overestimated. Furthermore, hosts can book their calendar by themselves (e. g. in the situation when they cannot offer their apartment for personal reasons), which is another reason for the overestimation of the occupancy data.

Secondly, the cost of the apartment can be adjusted as well. Moreover, in some cases, there is an extra guest fee for extra people accommodated in one apartment, which also misrepresents the real cost of the apartment per night in the datasets.

Because of the reasons mentioned above, I decided to create a new variable for Airbnb activity along with the lines of Sheppard, & Udell, (2016) to measure the Airbnb activity for each apartment that was sold between January 2014 and the September 2018. The procedure of getting these data is following.

4.2.2 Airbnb activity measure

For this procedure, I assume that once a listing became available, it has never exited the Airbnb market. Thus, I can compute the number of active listings around each sale[13] in the time of sale. Therefore, in order to consider all listings that might have influenced the sale price, all Airbnb listings which received the first review up to one month before the sale of the apartment are taken into account.

Firstly, I decided to specify the granularity of transaction data by month and year, and according to the location by Prague districts (Prague 1 to Prague 10). The information about specific Prague districts is not available in the Airbnb dataset, thus using JavaScript, the Prague districts were assigned to each of the listings according to its GPS coordinates.

Secondly, Airbnb dataset and transaction dataset were aggregated and joined together using JavaScript. Before working in JavaScript, Airbnb data were aggregated according to month and year when a listing received the first review. I decided to use the date of the first review as a date indicating when the listing became available. This date was set instead of the date when a listing was created because according to Brian Chesky, the CEO of Airbnb Inc., *"72% of hosts leave a*

[13]In other words, one transaction in the transaction prices dataset provided by Společnost pro cenové mapy, s. r. o.

review for hosts" after their stay (Chesky 2012). Thus, this date can be understood as a proxy for the first booking. From the original Airbnb dataset of 27 079 listings, 2 579 were removed because of the missing information about GPS coordinates, which is the crucial information for the data processing in JavaScript, or missing information about the type of accommodation. Another 1 504 listings received the first review after September 2018; thus they were also removed in order to correspond with the transaction dataset, which contains information about apartment sales from the year 2014 to the third quarter of the year 2018.

Using GPS coordinates from both datasets, I computed the number of active listings (listing became available at least one month before the actual sale) around each sale in the time of sale. Around each sale with the radius of 150, 300 and 500 meters[14] was computed the number of listings as a proxy for Airbnb activity. Besides, within the overall number of listings, I also distinguished among the types of accommodation. The number of listings around each sale was calculated separately for all listings, entire apartments, and shared or private rooms. These values were spatially joined to each sale from the transaction dataset in JavaScript. This procedure motivated by Sheppard & Udell (2016) is graphically explained in Illustration 1.

[14]To define a spatial area (polygon) in JavaScript, several GPS coordinates are needed for the determination of the area. Thus, these areas are in the shape of decagons.

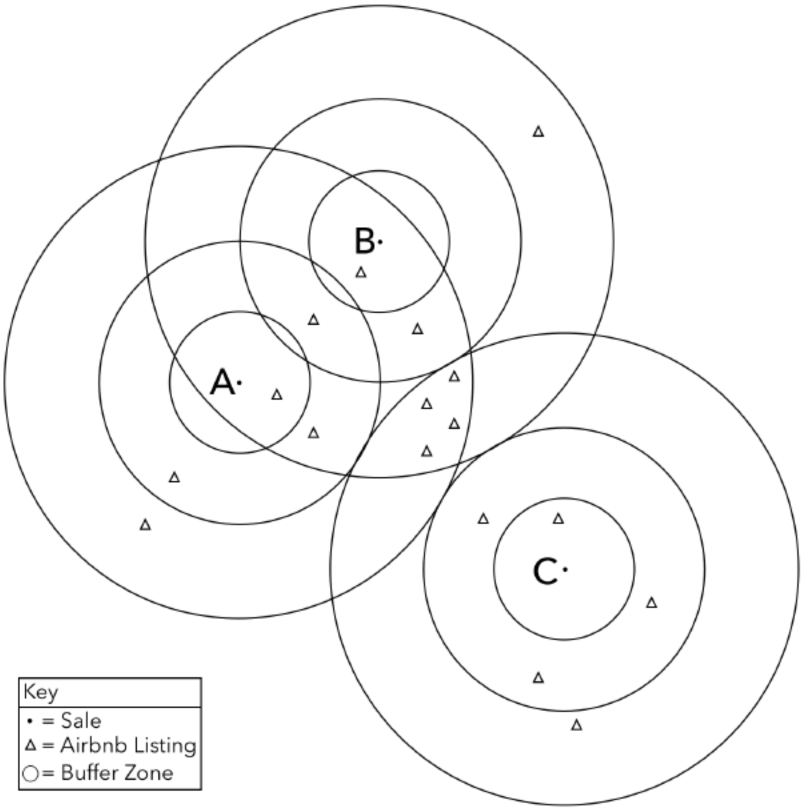

Illustration 1 – Sales & Buffer Zones, Sheppard et al. (2016)

For instance, the apartment A had in the time of sale one Airbnb listing in the buffer zone of 150 m, four listings in the buffer zone of 300 m and eleven listings in the 500 m buffer zone.

4.3 Criminality data

As a measurement of crime rate, I used the crime index. The crime index is a part of publicly available data about criminality in the Czech Republic, provided by Police of the Czech Republic and uploaded on mapakriminiality.cz by Otevřená společnost, o.p.s. The basic unit of time is a month, and the basic unit of the measurement of criminality is a district belonging to a local police department (Mapakriminality.cz 2019) Thus, the size of these districts is different from the size of the official districts in Prague defined by the cadastral office. In order to assign a correct crime index to a particular sale, each sale was matched with the distinct local police area according to its GPS coordinates. Therefore, I was able to compute the crime index for each sale in the time of sale. The index for each sale was computed as the average of indexes in a year before the sale in particular district to control for the criminality in the surroundings of each apartment in the time of the sale.

4.4 Noise data

I decided to use data from the night noise map because, in my opinion, the noise during the night would bother the residents more than noise during the day.

Unlike the criminality map which is divided into districts, the noise level in noise map can be comparable with contour lines in the touristic map, as displayed in Illustration 2. Thus, the procedure of matching the GPS coordinates of each apartment with the corresponding noise zone, where the GPS coordinates are located, would be misleading. The reason is that the larger the building, the quieter the zone where the GPS coordinates are located. This is also shown in Illustration 2 on the right side, where the small point represents the GPS coordinates of an apartment.

Therefore, the noise index was obtained by the following procedure: Firstly, the noise map was simplified that the boundaries of each polygon are straight lines, as displayed in Illustration 2. Secondly, the distances from each apartment to the boundary (kink point) of each of the nine levels were counted. Thirdly, a weighted average of the five noisiest areas was counted – the noise area of 60-65 dB to 80-85 dB with weights 1 to 5, respectively. Therefore, the noise index in this analysis is proxied by the weighted average of the shortest distances to five noisiest areas in proximity to an apartment. The outcome of this procedure is considered as a noise index.

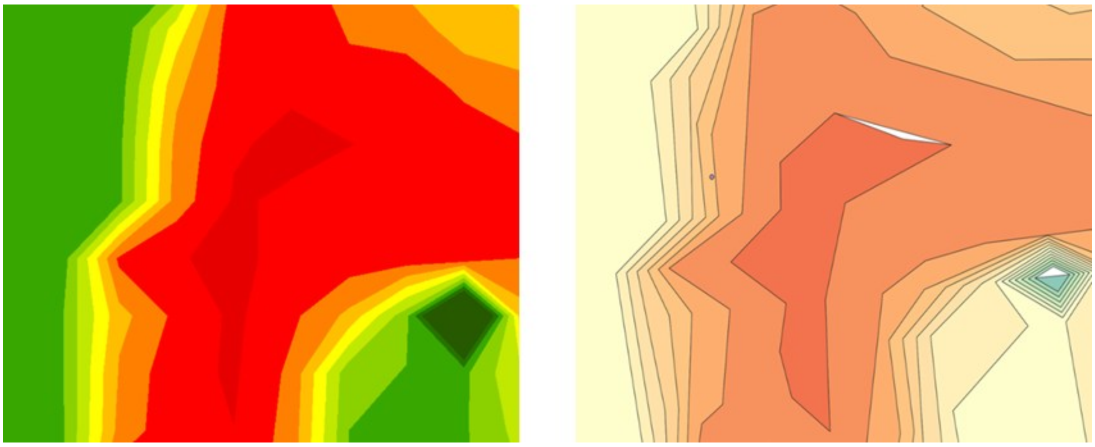

Illustration 2 – Left side – the example of noise map from http://mpp.praha.eu/app/map/atlas-zivotniho-prostredi/cs/hlukova-mapaIllustration, Right side – simplification of noise map, Jan Vlasatý, 2019

4.5 Descriptive statistics

Table 2 and Table 3 below contain the descriptive statistics, Table 2 summarizes the information from Airbnb dataset, while Table 3 details the Airbnb activity variable. In Table 3, descriptive statistics of selected controlled variables are also provided. Prices above detail the nightly prices of realized stays[15] in the ten districts in Prague from January 2018 to December 2018. From this dataset, 1.45% of data was removed because of the mean price within one month higher than 8 000 CZK. These data were removed for the purpose of this statistical analysis to show the approximate prices that tourists are on average or most often willing to pay for one night in Airbnb apartment or room in Prague. As expected, the highest average price per night is in the city center, Prague 1, followed by Prague 2, where the average nightly price is approximately 540 CZK less expensive. The difference in average nightly price among other districts does not differ substantially. The mean of received reviews of 27.05 confirms that Prague is a very popular location with a large base of Airbnb accommodation. Moreover, as mentioned in Subsection 4.2.1, the number of reviews is very likely underestimated.

[15] As I point out in section 4.2.1, the realized stay is defined as all the booked days in the calendar, thus it is not possible to distinguish between the number of days booked by guests and the number of days booked by hosts. Therefore, the prices in the statistics are very likely overestimated.

Table 3 details the controlled variables in the regressions. These descriptive statistics are made on transaction data from Prague 1 to Prague 10; thus, they are based on 42 974 sales from January 2014 to September 2018. Price for m^2 is listed instead of the sale price. "All in" variable contains all the listings (private rooms, shared rooms, and entire apartments) available in the Airbnb dataset.

Variable	Mean	Median	SD	Min	Max
Bedrooms	1.30	1.00	0.87	0.00	15.00
Capacity	3.85	4.00	2.32	0.00	30.00
Reviews	27.05	10.00	40.98	0.00	367.00
Price[16] Praha 1	2 332.92	2 000.00	1 383.12	203.90	7 989.78
Price Praha 2	1 788.32	1 471.47	1 184.34	220.00	7 991.00
Price Praha 3	1 416.42	1 187.72	921.14	100.00	7 939.60
Price Praha 4	1 218.05	1 000.00	819.45	208.67	7 612.90
Price Praha 5	1 537.65	1 245.25	1 054.93	214.64	7 990.00
Price Praha 6	1 282.49	1 015.28	871.20	232.00	7 861.17
Price Praha 7	1 266.25	1 065.39	781.73	225.00	7 735.00
Price Praha 8	1 467.07	1 205.83	959.15	220.30	7 995.00
Price Praha 9	1 152.39	999.00	666.96	217.00	5 565.00
Price Praha 10	1 219.50	1 002.74	791.05	210.00	7 286.33

Table 2 - Airbnb descriptive statistics

[16] Price in CZK

Variable	Mean	SD	Min	Max
Price for m^2	65 786.77	23 512.28	20 000.00	391 459.10
Floor area	65.77	31.53	10.80	707.20
Crime index	42.39	47.08	11.34	845.94
Distance to station	156.44	85.31	2.00	671.00
Distance to park	2 714.10	1 754.66	53.00	6 871.00
Noise index	1 672.26	1 917.63	85.00	43 583.00
All in 150	8.91	19.53	0.00	234.00
All in 300	29.48	63.32	0.00	713.00
All in 500	69.09	148.79	0.00	1 499.00
Entire home within 150 m	6.87	15.25	0.00	162.00
Entire home within 300 m	22.49	48.88	0.00	533.00
Entire home within 500 m	52.44	114.11	0.00	1 163.00
Private rooms within 150 m	1.92	4.74	0.00	76.00
Private rooms within 300 m	6.53	14.78	0.00	188.00
Private rooms within 500 m	15.51	34.38	0.00	361.00
Shared rooms within 150 m	0.13	0.73	0.00	37.00
Shared rooms within 300 m	0.46	1.73	0.00	52.00
Shared rooms within 500 m	1.14	3.19	0.00	82.00

Table 3 - Descriptive statistics of variables used in the regressions

5 Methodology

5.1 Hedonic regression

For the empirical part of this thesis, the hedonic pricing regression motivated by Sheppard & Udell, (2016) is used to estimate the impact of Airbnb on residential prices in Prague. The approach of a hedonic price was firstly presented by Rosen, (1974) in his study "Hedonic Pricing and Implicit Markets: Product Differentiation in Pure Competition", although the first signs of the hedonic model can be found in Hall (1922) who aims to value the price of farmland in Blue Earth County, Minnesota. There are other authors who had been concerned with hedonic regression before Rosen, for instance Court (1939), who is widely considered as a father of hedonic regression mainly thanks to his analysis of automobile price indexes, or Lancaster (1966), who attempts to employ a theoretical base for hedonic regression (Sopranzetti 2015).

The hedonic price is defined as the individual prices of attributes, that determine the property value (Rosen 1974). In the case of hedonic pricing regression concerning the housing market, the value of the dwelling is determined by a set of characteristics such as local amenities, floor area, number of bedrooms or bathrooms, neighborhood quality, etc. More detailed theoretical description of the hedonic pricing model can be found in Follain, & Jimenez, (1985), Epple, (1987) or Sheppard (1999).

5.2 Model

The hedonic regression is estimated using ordinary least squares method, as well Rod et al., (2018) or Sheppard & Udell (2016). The unit of observation in this analysis is an individual sale which took place in Prague, specifically in the ten main districts Prague 1 to Prague 10, between January 2014 and September 2018. From the original dataset of 67 680 observations, 214 was dropped because the date of sale was out of the observed period and 24 672 observations were dropped because the location was out of the area of districts Prague 1 to Prague 10, leaving 42 795 observations in total.

In the model, where the dependent variable is the sale price, the explanatory variables such as floor area, criminality rate, type of building, distance to the nearest public transport stop, distance to park, and ambient noise are included. The main explanatory variable added in the model is the Airbnb activity. As a proxy for Airbnb activity is used the number of Airbnb listings around each sale in a radius of 300m up to one month before the sale. Also, dummy variables for years to capture the time trend, and dummy variables for a location to capture the time-invariant neighborhood quality or attractiveness of the district are added. The neighborhood quality is widely considered as a significant factor influencing the sale prices, as concluded in Yan & Zhang (2006). The variables $Floor\ area$ and $Building\ type$ are included as the crucial factors influencing the sale price of an apartment. Moreover, noise, crime index and two types of distances are included to control for micro-neighborhood externalities, that could have influenced the sale prices, as suggested by Mingche & Brown (1980).

Generally, in hedonic pricing models, the issues of heteroskedasticity and endogeneity arise (Sheppard & Udell 2016). To test the heteroskedasticity, the Breusch-Pagan test was employed. This test showed the heteroskedasticity in the model. As a remedy, robust standard errors are included in all tables across this paper. The second mentioned issue is endogeneity in the model since the correlation between the error term and the number of Airbnb listings may arise. If there is a factor positively correlated with Airbnb activity and it is unexplained by the model, this coefficient might be overestimated. The proof that there is not a relationship between these variables is extremely difficult.

Moreover, since the cross-sectional data are used in the model, endogeneity cannot be properly tested. The cause of endogeneity might be the omitted variables, which can be related to explanatory variables in the model. To be specific, presence of elevator and floor, where the apartment is located, could be correlated with $building\ type$. Thus, $building\ type$ might be overestimated in this regression. Unfortunately, as will be mentioned in Subsection 6.1, these data are not available, thus could have not been used in this analysis. However, I do not assume that the floor, where the apartment is located, or the presence of an elevator would be correlated with the number of Airbnb listings. Therefore, these omitted variables most likely do not cause the endogeneity of variable Airbnb activity.

The dependent variable is the natural logarithm of the sale price, as well as the main variable of interest Airbnb activity to better interpret the resulting relationship. Only the sales of apartments located in one of the districts of Prague 1 to Prague 10 are included in the multiple linear regression model, where the Airbnb accommodation is mostly situated. I do not assume that shared or private rooms offered on the Airbnb website would have influenced residential prices, thus only the entire apartments in the radius of 300m around each sale are included in the model. However, to show the robustness of the estimates and assumptions, all three types of listings are included in several models in Chapter 6.

For model estimation, as well as for data processing, the essential assumption is made along the lines with Sheppard & Udell, (2016). I assume that once a listing became available, it has never exited the Airbnb market. Therefore, the number of Airbnb listings around each sale in the time of the sale can be determined. In view of the fact that this assumption may overestimate the number of listings around each sale, mainly because I cannot control when a listing exited the market, a few different models will be provided in Chapter 6 and to show the robustness of the results. The other limitation of this model is the fact that listings, that exited the Airbnb market before the year 2016 cannot be included, since this dataset consists of listings available on the website from 2016, as mentioned in Subsection 4.2.1.

The OLS regression has the following form:

$$\begin{aligned}
\ln(Sale\ price_{idmt}) = {} & \alpha + \beta_1 \ln(Airbnb\ activity_{im}) + \beta_2 \ln(Floor\ area_i) + \\
& + \beta_3 \ln(Noise_i) + \beta_4 \ln(Crime_{it}) + \gamma_1(Building\ type_i) + \\
& + \beta_5 \ln(Distance\ to\ station_i) + \beta_6 \ln(Distance\ to\ park_i) + \\
& + \gamma_2(Year\ of\ Sale_{it}) + \gamma_3(District_{id}) + \epsilon_{idmt}
\end{aligned}$$

In the model, $ln\ (Sale\ price_{idmt})$ is a nature logarithm of apartment i´s sale price in month m and year t in district d. The scalar coefficient is represented by β while the vector coefficient is represented by γ because $Building\ type$ is a categorical variable, $Year$ contains the set of dummy variables representing years and $District$

contains the set of dummy variables representing the location (districts Prague 1 to Prague 10). All variables used in the model, as well as their description, are listed in Table 4.

Variable	**Description**
Sale price	The dependent variable, it represents transaction price of a sale of an apartment that took place between January 2014 and September 2018
Airbnb activity	Airbnb activity is represented by the number of Airbnb listing around each sale in the time of sale. In the main model, only entire apartments are taken into account.
Floor area	The floor area of an apartment in m^2.
Noise	Noise index is represented as a weighted average of distances to the noisiest area in Prague during the night. Five noisy areas are considered, from 60-65 DB to 80-85 DB, each of the areas is weighted by 1 to 5, respectively. Thus, the higher the weighted distance, the quieter the surroundings of the apartment.
Crime	Crime index represents the level of criminality in the surroundings of the apartment. The index is counted as the average of monthly crime indexes during the year before the sale.
Building type	Three types of building are represented by this variable – brick house, prefabricated (panel) building and new building.
Distance to station	Distance to the nearest public transport stop (either bus stop, tram station or subway entrance)
Distance to park	Distance to the nearest park. The largest parks are taken into account e. g. Letná, Stromovka, Petřín, etc.
Year	Set of dummy variables for years, capturing the time trend in the regression.
District	Set of dummy variables for location, capturing the time-invariant characteristics of the district.

Table 4 – Description of variables used in the model

6 Results

6.1 Prague 1 to Prague 10

The main results of this analysis are displayed in Table 5, where the dependent variable is the natural logarithm of *Sale price* and all explanatory variables, besides indicator variables, are logarithmically transformed. As explained in Chapter 5, I control for the floor area, type of building, criminality index and noise index of the apartment's surroundings, several distances to important places, an indicator for time to capture the time-trend and indicator for districts to capture the time-invariant quality and attractiveness of the neighborhood.

The results show that all non-indicator variables are statistically significant, except for variable *Distance to station*. I decided to include this variable in the model because the distance to public transport stops is a very important aspect when buying a new apartment, but the reason why it has not shown to be significant can be the high density of bus stops, tram stops or metro stations in districts Prague 1 to Prague 10. Moreover, on the global scale, Prague was ranked on the fifth place in the analysis of cities mobility index, which compares many aspects of urbans transport system in cities all over the world (Arcadis 2017).

As a base for indicators of *District* is used district Prague 10 as a group with the highest number of observations. Indicators for Prague 7 and 8 have shown to be insignificant, probably because the sale prices are very similar as in Prague 10. Predictably, the indicator variables for location shows that in the city center, Prague 1, the sale prices are the highest in Prague. Indicators for building type includes three factors – brick house, which is considered as a base indicator, prefabricated (panel) house and new building. In the dataset, building type of 262 apartments was marked as the burgher house[17], very old house typical for the city center, Prague 1. Due to the small number of observations, this building type was replaced by a brick house for the purposes of this analysis.

[17] In Czech, burgher house stands for „měšťanský dům“.

The main variable of interest, Airbnb activity, proxied by the number of entire apartment listings within 300m, is significant. Thus, the a 1% increase in Airbnb activity leads to an increase in the sale price of an apartment by 0.0423%, ceteris paribus, at 0.1% significance level. However, there are several important limitations that must be taken into account. First, the problem of omitted variable bias probably arises, since the variables such as the elevator in the building and the floor, where the apartment is located, are not included. Unfortunately, these data are not available for Prague apartments. There is The Registry of Territorial Identification, Addresses and Real Estates provided by Czech Office for Surveying, Mapping, and Cadastre where such information exists, but the registry is incomplete, and some information is not correct, thus I cannot use these data in my model.

The significance and the signs of the other variables are as expected. Although $noise$ is proxied by the distances, it has the opposite sign as $distance\ to\ park$, because in this case, the higher the distance from the noisiest area, the better the location of the apartments, thus the higher the prices.

Besides the results from the main model, results from two slightly different models are included in Table 5 to show the robustness of the results. Model (2) contains variables for a number of shared and private rooms around each sale. As expected, the Airbnb activity proxied by the number of shared rooms is not significant, since the portion of shared rooms is just 2% of all Airbnb listings. The last Model (3) in Table 5 displays the result from the model, where Airbnb activity is proxied by the number of bedrooms around each sale. The estimated coefficient of Airbnb activity is slightly smaller, increase in Airbnb activity leads to approximately 0.0381% increase in sale prices. This is given by the fact that the information about the number of bedrooms is not available for all Airbnb listings in the Airbnb dataset. Out of 22 996 listings, 19 579[18] contain information about the number of bedrooms.

[18] In the dataset, bedrooms of 138 apartments were marked as "studio". These listings are considered as listings with one bedroom.

In addition, Table 8 shows the results, where outliers of the sale price in the datasets were removed. From the dataset of 42 794 observations, 1 556 were dropped because of the price higher than 10 875 000 CZK (approximately 3.6% of data). The results based on the dataset remain robust. Table 8 with the results of the models without outliers are provided in Appendix A.

Variable	Model 1	Model 2	Model 3
Intercept	11.1296*** 0.0672	11.0953*** 0.0675	11.1670*** 0.0659
ln(Floor area)	0.9400*** 0.0064	0.9402*** 0.0063	0.9387*** 0.0068
ln(1 + Number of entire home listings within 300m)	0.0423*** 0.0021	0.0355*** 0.0024	
ln(1 + Number of private room listings within 300m)		0.0118*** 0.0029	
ln(1 + Number of shared room listings within 300m)		0.0011 0.0043	
ln(1 + Number of bedrooms within 300m)			0.0381*** 0.0019
ln(Crime)	0.0275*** 0.0049	0.0297*** 0.0049	0.0270*** 0.0049
ln(Noise)	0.0370*** 0.0058	0.0389*** 0.0058	0.0351*** 0.0058
Indicator for building type - New building	0.2253*** 0.0119	0.2270*** 0.0118	0.2262*** 0.0119
Indicator for building type - Prefabricated (panel) buildings	-0.0283*** 0.0063	-0.0282*** 0.0062	-0.0289*** 0.0063
ln(Distance to station)	-0.0037 0.0030	-0.0038 0.0030	-0.0045 0.0029
ln(Distance to park)	-0.0687*** 0.0045	-0.0672*** 0.0045	-0.0707*** 0.0044
Indicator for year 2015	0.0460*** 0.0057	0.0461*** 0.0056	0.0464*** 0.0057
Indicator for year 2016	0.1233*** 0.0068	0.1199*** 0.0068	0.1252*** 0.0068
Indicator for year 2017	0.2046*** 0.0068	0.1992*** 0.0085	0.2080*** 0.0086
Indicator for year 2018	0.3022*** 0.0104	0.2962*** 0.0104	0.3069*** 0.0104
Indicator for district Prague 1	0.3629*** 0.0289	0.3612*** 0.0288	0.3616*** 0.0289
Indicator for district Prague 2	0.1390*** 0.0118	0.1362*** 0.0117	0.1371*** 0.0118
Indicator for district Prague 3	-0.0185** 0.0062	-0.0182** 0.0062	-0.0171** 0.0062
Indicator for district Prague 4	0.0263*** 0.0065	0.0263*** 0.0065	0.0264*** 0.0065
Indicator for district Prague 5	-0.0264*** 0.0073	-0.0256*** 0.0074	-0.0255*** 0.0073
Indicator for district Prague 6	0.1022*** 0.0085	0.1023*** 0.0085	0.1027*** 0.0084
Indicator for district Prague 7	0.0072 0.0098	0.0058 0.0097	0.0103*** 0.0098
Indicator for district Prague 8	-0.0061 0.0058	-0.0060 0.0058	-0.0041*** 0.0058
Indicator for district Prague 9	-0.0284*** 0.0058	-0.0260*** 0.0058	-0.0248*** 0.0057
R^2	0.8091	0.8092	0.8089
Adjusted R^2	0.8090	0.8091	0.8088
Number of observations	42 794	42 794	42 794

Significance codes: ***p < 0.001, **p < 0.01, *p < 0.05
Robust standard errors are included below the estimates.

Table 5 – Main results

6.2 Prague 1

Since the issue of Airbnb in Prague resonates the most in the context of the city center, Prague 1, I decided to include the model specifically for this district. This model is based on 1 459 transactions in the district Prague 1 from January 2014 to September 2018. Table 6 displays the results of this model. Again, a few other models with different specifications are included. Model (7) shows the results from the original model, Model (8) shows the original model based on the dataset without outliers, Model (9) contains the number of bedrooms as a proxy for Airbnb activity and Model (10) displays the same Model as (9) based on dataset without outliers. As outliers are determined transactions above 20 162 500 CZK, which is approximately 5.3% of the data. The results show that the 1% increase in Airbnb activity leads to between 0.0711% and 0.0816% increase in sale prices, significant at 0.1% level, depending on the proxy for Airbnb activity and involved outliers.

Interestingly, the variable *Crime* is insignificant, although the criminality rate in the city center is relatively high with respect to other districts. The variable *building type* contains only two factors in this model, the brick house, which is a base indicator, and a new building, since there are no prefabricated (panel) houses in the city center. As mentioned in the previous section, the building type of 262 observations defined as "burgher house" in Prague 1 was replaced by brick house. Nevertheless, the same limitations as for the original model must be taken into account. Moreover, the dataset is much smaller in comparison to the number of observations in other districts. The significance of years corresponds with the Figure 1, where the prices for apartments in Prague 1 boosted in 2017 and 2018.

Variable	Model 7	Model 8	Model 9	Model 10
Intercept	10.6892*** 0.3001	10.6078*** 0.3043	11.1051*** 0.2263	11.0340*** 0.2324
ln(Floor area)	0.8992*** 0.0232	0.8994*** 0.0233	0.8169*** 0.0216	0.8171*** 0.0216
ln(Crime)	-0.0264 0.0161	-0.0261 0.0165	-0.0283 0.0155	-0.0280 0.0159
ln(Noise)	0.3035*** 0.0363	0.3129*** 0.0372	0.2760*** 0.0331	0.2844*** 0.0339
ln(1 + Number of entire home listings within 300m)	0.0816*** 0.0201		0.0726*** 0.0211	
ln(1 + Number of bedrooms within 300m)		0.0798*** 0.0207		0.0711 0.0219
Indicator for building type - New building	0.2780*** 0.0661	0.2754*** 0.0662	0.2475*** 0.0568	0.2450*** 0.0568
ln(Distance to park)	0.1683*** 0.0540	-0.1645*** 0.0304	-0.1534*** 0.0260	-0.1542*** 0.0261
ln(Distance to station)	-0.0002 0.0164	-0.0005 0.0164	0.0133 0.0141	0.0129 0.0141
Indicator for year 2015	0.0114 0.0258	0.0101 0.0264	0.0326 0.0267	0.0315 0.0275
Indicator for year 2016	0.0764 0.0472	0.0780 0.0467	0.0949* 0.0461	0.0962* 0.0464
Indicator for year 2017	0.1549** 0.0559	0.1553** 0.0555	0.1683** 0.0540	0.1685** 0.0551
Indicator for year 2018	0.2650*** 0.0566	0.2674*** 0.0581	0.2928*** 0.0600	0.2948*** 0.0619
R^2	0.7542	0.7544	0.7090	0.7091
Adjusted R^2	0.7517	0.7519	0.7067	0.7068
Number of observations	1 459	1 459	1 381	1 381

Significance codes: ***p < 0.001, **p < 0.01, *p < 0.05

Robust standard errors are included below the estimates.

Table 6 – Prague 1 main results

6.2.1 Comparison of the results

This Subsection is provided to compare the results from Section 6.1 and Section 6.2. In Table 7 only the coefficients of the main variable of interest Airbnb activity in different models are provided as proxied by the number of entire homes, private rooms, shared rooms or bedrooms or their combination. As displayed, all results besides the proxy Shared rooms, are statistically significant at 0.1% level. Again, robust standard errors are depicted below the estimates. There are displayed the results from four tables, based on the dataset used. Below each name of the observed location is stated the table, where the depicted results come from.

	Airbnb activity proxy			
	Entire homes	Private rooms	Shared rooms	Bedrooms
Prague Table 5	0.0423*** 0.0021			
	0.0355*** 0.0024	0.0118*** 0.0029	0.0011 0.0043	
				0.0381*** 0.0019
Prague WO[19] Table 8	0.0431*** 0.0021			
	0.0361*** 0.0024	0.0099*** 0.0028	0.0087 0.0044	
				0.0388*** 0.0019
Prague 1 Table 6	0.0816*** 0.0201			
				0.0798*** 0.0207
Prague 1 WO[19] Table 6	0.0726*** 0.0211			
				0.0711** 0.0219

Table 7 – Comparison of the results

[19] Based on the dataset without outliers.

6.3 Airbnb in Prague over time

In addition, interaction terms of Airbnb activity and Year are included in the model to inspect how the relationship between Airbnb activity and residential prices may have changed over time. In general, interaction terms involving dummy variables are used in the model to test for group differences (Wooldridge, 2012). In this model, interaction terms show the additional effect that Airbnb activity might have had over time. For this model, the dataset without outliers (e. i. transactions above 10 875 000 CZK) was chosen to examine the Airbnb effect over time, since the scope of this analysis is to determine the potential impact of Airbnb on residential prices, affordable for the middle class. The results show that interaction terms of Airbnb activity and the years 2015 and 2016 are not insignificant, while interactions covering the years 2017 and 2018 are significant. Furthermore, the results show that the coefficient of the main variable slightly increased from 2017 to 2018 which probably corresponds to the increasing number of Airbnb listings which entered the Airbnb market during these years. Thus, during years 2014 – 2016, the effect of Airbnb did not changed, since the interaction terms are not significant (thus, a 1% increase in Airbnb activity leads to between 0.0279% to 0.0352% increase in residential prices, ceteris paribus), whereas in 2017, a 1% increase in Airbnb activity leads to an additional increase in sale prices by 0.0135% to 0.0195% and in the year 2018 0.0175% to 0.0268%, ceteris paribus, depending on the proxy for Airbnb activity. Table 9 in Appendix B provides the results of these models.

7 Conclusion

This thesis examined the relationship between the number of Airbnb listings and residential prices in Prague. I employed the hedonic regressions using publicly inaccessible transaction dataset containing every single transaction of sale of an apartment in Prague from January 2014 to September 2018, Airbnb dataset and several publicly accessible datasets containing Prague city data to control for several characteristics influencing the sale prices. The hypotheses were tested based on the dataset including observations only from districts Prague 1 to Prague 10, where the Airbnb listings are mostly located. The results showed that a 1% increase in Airbnb activity led to between 0.0381% and 0.0423% increase in sale prices depending on the proxy for Airbnb activity. Moreover, in the city center district, Prague 1, a 1% increase in Airbnb activity led to between 0.0711% and 0.0816% increase in residential prices, which also supports the second hypotheses, that the impact of Airbnb on residential prices is higher in the city center than in Prague as a whole. Lastly, I found out that Airbnb impact has significantly arisen in recent years, especially in 2017 and 2018. Therefore, all hypotheses were not rejected.

Since one of the recent issues of the sharing economy is regulation, I would like to emphasize, that the thesis has not aimed to suggest if regulatory framework should be set or not, however, it provides complex data analysis of the situation in Prague crucial for regulatory approach decision-making. This thesis importantly contributes to a very rarely explored sector of the sharing economy, namely of the sharing accommodation, as one of the first empirically based analysis of the impact of Airbnb on the residential market in Prague.

However, some limitations of this research must be taken into consideration. Firstly, as in other hedonic regression, the problem of the endogeneity might arise. Secondly, in the Airbnb dataset, I cannot involve the listings, which had exited the market before the scraping data begins, that is before 2016. Thirdly, the results of this research might be overestimated, since I cannot control when the Airbnb listing exited the market.

Since the topic of the sharing accommodation and its impact, mostly Airbnb, is a subject of current discussions, more data-based research should be made concerning this issue. Moreover, since the Prague data platform Golemio measured that the number of Airbnb listings in Prague has started to decrease (Golemio 2018), more analysis focusing on the above-mentioned limitations should be done to measure the potential change in the impact of Airbnb on residential prices in the future.

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Appendix A

Variable	Model 4	Model 5	Model 6
Intercept	11.2810***	11.2453***	11.3218***
	0.0703	0.0701	0.0690
ln(Floor area)	0.8751***	0.8759***	0.8738***
	0.0062	0.0062	0.0062
ln(1 + Number of entire home listings within 300m)	0.0431***	0.0361***	
	0.0021	0.0024	
ln(1 + Number of private rooms listing within 300m)		0.0099***	
		0.0028	
ln(1 + Number of shared room listings within 300m)		0.0087	
		0.0044	
ln(1 + Number of bedrooms within 300m)			0.0388***
			0.0019
ln(Crime)	0.0276***	0.0301***	0.0271***
	0.0047	0.0047	0.0048
ln(Noise)	0.0337***	0.0356***	0.0316***
	0.0056	0.0055	0.0055
Indicator for building type - New building	0.2108***	0.2128***	0.2119***
	0.0115	0.0115	0.0115
Indicator for building type - Prefabricated (panel) buildings	-0.0312***	-0.0308***	-0.0318***
	0.0061	0.0060	0.0061
ln(Distance to station)	0.0023	0.0022	0.0016
	0.0025	0.0025	0.0025
ln(Distance to park)	-0.0554***	-0.0538***	-0.0575***
	0.0041	0.0041	0.0040
Indicator for year 2015	0.0470***	0.0476***	0.0475***
	0.0057	0.0057	0.0057
Indicator for year 2016	0.1199***	0.1171***	0.1220***
	0.0068	0.0069	0.0069
Indicator for year 2017	0.2008***	0.1957***	0.2044***
	0.0085	0.0087	0.0087
Indicator for year 2018	0.2813***	0.2759***	0.2864***
	0.0094	0.0095	0.0097
Indicator for district Prague 1	0.3049***	0.3036***	0.3030***
	0.0244	0.0242	0.0245
Indicator for district Prague 2	0.1375***	0.1358***	0.1356***
	0.0121	0.0120	0.0122
Indicator for district Prague 3	-0.0092	-0.0077	-0.0078
	0.0059	0.0060	0.0060
Indicator for district Prague 4	0.0116*	0.0117*	0.0117*
	0.0048	0.0049	0.0049
Indicator for district Prague 5	-0.0199**	-0.0182**	-0.0190**
	0.0068	0.0068	0.0068
Indicator for district Prague 6	0.0974***	0.0986***	0.0981***
	0.0080	0.0079	0.0080
Indicator for district Prague 7	0.0163	0.0168	0.0196
	0.0101	0.0099	0.0101
Indicator for district Prague 8	-0.0058	-0.0053	-0.0036
	0.0056	0.0056	0.0056
Indicator for district Prague 9	-0.0312***	-0.0289***	-0.0275***
	0.0055	0.0057	0.0055
R^2	0.7750	0.7753	0.7748
Adjusted R^2	0.7749	0.7751	0.7746

Number of observations	41 238	41 238	41 238

Significance codes: ***p < 0.001, **p < 0.01, *p < 0.05
Robust standard errors are included below the estimates.

Table 8 – Results from the original model based on dataset without outliers

Appendix B

Variable	Model 11	Model 12
Intercept	11.3141*** 0.0688	11.3604*** 0.0666
ln(Floor area)	0.8755*** 0.0061	0.8744*** 0.0061
ln(1 + Number of entire home listings within 300m)	0.0352*** 0.0049	
ln(1 + Number of bedrooms within 300m)		0.0267*** 0.0039
ln(Crime)	0.0263*** 0.0047	0.0254*** 0.0047
ln(Noise)	0.0313*** 0.0054	0.0288*** 0.0054
Indicator for building type - New building	0.2100*** 0.0115	0.2111*** 0.0114
Indicator for building type - Prefabricated (panel) buildings	-0.03190*** 0.0060	-0.0329*** 0.0060
ln(Distance to station)	0.0024 0.0025	0.0017 0.0025
ln(Distance to park)	-0.0562*** 0.0041	-0.0579*** 0.0040
Indicator for year 2015	0.0585*** 0.0058	0.0571*** 0.0059
Indicator for year 2016	0.1256*** 0.0076	0.1205*** 0.0080
Indicator for year 2017	0.1779*** 0.0107	0.1645*** 0.0116
Indicator for year 2018	0.2444*** 0.0133	0.2192*** 0.0142
Indicator for district Prague 1	0.3173*** 0.0249	0.3190*** 0.0244
Indicator for district Prague 2	0.1411*** 0.0123	0.1393*** 0.0122
Indicator for district Prague 3	-0.0062 0.0059	-0.0047 0.0060
Indicator for district Prague 4	0.0113* 0.0049	0.0105* 0.0049
Indicator for district Prague 5	-0.0174* 0.0067	-0.0161* 0.0067
Indicator for district Prague 6	0.0981*** 0.0079	0.0985*** 0.0079
Indicator for district Prague 7	0.0202* 0.0099	0.0235* 0.0099
Indicator for district Prague 8	-0.0041 0.0056	-0.0020 0.0056
Indicator for district Prague 9	-0.0297*** 0.0055	-0.0251*** 0.0056
Airbnb Activity*year 2015	-0.0050 0.0049	-0.0015 0.0041

Airbnb Activity*year 2016	0.0020 0.0046	0.0069 0.0038
Airbnb Activity*year 2017	0.0135* 0.0054	0.0195*** 0.0046
Airbnb Activity*year 2018	0.0175** 0.0060	0.0268*** 0.0051
R^2	0.7755	0.7757
Adjusted R^2	0.7754	0.7756
Number of observations	41 238	41 238

Significance codes: ***p < 0.001, **p < 0.01, *p < 0.05

Robust standard errors are included below the estimates.

Table 9 – Airbnb activity over time – results