How Airbnb will affect housing conditions in Budapest?

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Abstract

The huge gain in popularity and usage of short-term rental marketplaces (such as Airbnb) created an ongoing debate between residents, property owners and regulators as the conversion of residential housing units to Airbnb listings seem to have effects on housing prices, causing or amplifying other indirect effects such as gentrification and urban transformation. In this thesis I predict the possible effect of Airbnb on rental prices in Budapest for the next 5 years, assuming that the current growth of listings will continue and that the share of Airbnb listings will catch up at least by current Western Europe and US tourist destinations. I combine an agent-based model with a supply-side price elasticity pricing mechanism and predict that overall rental prices in Budapest will increase by 3.21% due to Airbnb. I also show that the most affected districts will be the downtown ones (VI-VII-VIII) and that the spillover and urban transformation effect will cause high rental price increases in the outermost districts, where prices are currently the lowest.

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Introduction

There is an escalating discussion and debate regarding the various effects of the sharing economy. As the biggest players in the field are growing enormously, disrupting their industries, researchers are trying to grasp, measure, and forecast the different effects they have on their field, including the influence on incumbents, the whole industry, and other spillover effects on the society. Decision-makers are also facing difficulties addressing the new challenges posed by these companies and drawing up substantiated policy recommendations, as the rapid growth of the sharing economy market makes it difficult to gather relevant prior data on market effects. To get the extent of this growth, Airbnb and Uber, two of the largest international players, are already multi-billion companies with valuations around $35 billion[1] and $70 billion[2] and they still have ~50% year/year growth.

Narrowing the focus on home-sharing companies, Airbnb, the largest short-term rental (STR) marketplace in the world, has 150 million users, more than 6 million listings worldwide, of which 1.9 million are instantly bookable[3]. In comparison, Hilton, Marriott, and Intercontinental, 3 of the 5 largest hotel chains in the world, has a combined capacity of less, than 3 million rooms[4]. A disruption of this size on the housing and hospitality market has its consequences though. Three of the most studied effects recently are the revenue effects in the hospitality industry (see Zervas, Proserpio, and Bryers (2017)), the gentrification effect and the restructuring of the city landscapes (see Wachsmuth, and Weisler (2018) and Garcia-Ayllon

[1] https://ipropertymanagement.com/airbnb-statistics/
[2] https://finance.yahoo.com/quote/UBER?p=UBER
[3] https://ipropertymanagement.com/airbnb-statistics/
[4] https://www.ihgplc.com/en/about-us/our-global-presence
https://en.wikipedia.org/wiki/Marriott_International
https://eu.usatoday.com/story/travel/hotels/2018/03/12/brands-and-hotel-rooms-hilton-hotels-and-resorts-numbers/415784002/

(2018)), and the price and supply effects on the residential housing market (see Barron, Kung, and Proserpio (2017) and Horn, and Merante (2017)).

The original goal of Airbnb were twofold: Providing extra revenue for residents by renting out their ”spare” housing capacity, e.g. extra rooms or whole apartments when they are temporarily vacant, and offering an extra supply of hospitality options, mainly for tourists. However, landlords and investors realized that there is an extra income opportunity in the short-term rental market, so they either acquired housing units or converted their apartments from long-term rental offerings to the STR market. Wachsmuth, and Weisler (2018) shows that in New York City, Airbnb revenues in tourist destinations can reach 200-300% of the median rents in the same area. An analysis from portfolio.hu shows that even in Budapest, property owners may generate 50-70% extra revenue from letting their houses on the STR market. As a result of this phenomenon, 64% of the Airbnb listings in Los Angeles are never occupied by residents (Lee (2016)). This number may be even higher in Budapest, where 89% of the listings are entire homes (a share much larger than in Los Angeles (69%), New York (56%), London (61%), or Barcelona (59%)) and 73% of all rentals are available for at least 120 days a year (compared to 50-70% in the aforementioned cities)[5]. One obvious consequence of this is that a significant increase in the number of Airbnb listings causes a drop in the supply for long-term rentals. The market consequences of this is worthy of further investigation and research.

Most of the existing literature on residential house prices and rents are focusing on past effects in markets with the largest Airbnb penetration, namely the United States or some popular tourist destination in Western Europe. In contrast, I measure and predict the possible effects of short-term rentals on long-term rental prices and housing affordability in Budapest, a city where phenomenon of home-sharing is less common, but both its growth and the demand from tourists

[5] Data from https://www.airdna.co

are constantly increasing (Boros et al. (2018)). I present an agent-based model with a setup mirroring the current conditions in Budapest, including housing, family income, and other parameters. The model focuses on the price implications of what Airbnb may generate through the fall of long-term rental supply for residents and the additional commuting time families incur due to the "hotelization" of downtown districts. I run 2,000 simulations in different scenarios to analyse the extent and severity of the consequences should Airbnb decrease the aforementioned rental supply stock in the town. I show that the downtown area, where most of the Airbnb listings are, is the most affected as rental prices could increase by 8.3-10.7%. Additionally, a large shock to the housing market (a large growth of Airbnb) could cause strong spillover effects in suburban areas, up to 6%, decreasing the affordable housing stock and forcing families out of the town.

I perform a regression tree-based analysis besides and assess the summary statistics to investigate the price responses in different scenarios and evaluate the importance of the input variables. I also highlight a special setup to present forecasts if Budapest gets in a situation as Barcelona is in right now. Barcelona is a popular tourist destination with a well-developed short-term rental market[6], similar in size and owner-occupation to Budapest. Furthermore, there are reference results to compare to as Segú (2018) argues that STR increased rent prices in Barcelona by 4%. My model predicts a 4.05% increase of rental prices in Budapest in this scenario.

Overall, this paper contributes to the literature in two main ways. First, it measures and forecasts the possible rental price effects of home-sharing in a city which has not been examined thoroughly yet. Second, the approach taken is different as this thesis introduces an agent-based

[6] Based on https://www.airdna.co/vacation-rental-data/app/es/barcelona/barcelona/overview, short-tern rental offerings in Barcelona has only a mild growth in recent years

simulation and rental price elasticity instead of a hedonic regression estimation utilized in previous research papers.

The structure of this paper is as it follows: Chapter 1 provides an overview of the previous literature about the short-term rental market. In Chapter 2, the methodology and present the data sources used to set up the model are described. In Chapter 3, various results are presented, compared to previous findings and policy recommendations are provided. In Chapter 4, the conclusion, the consideration of possible extensions of this model, and examination of options for further analysis and research in this field are presented. All figures, tables, and statistics can be found in the Appendix.

1. Literature review

1.1. Peer-to-Peer and Short-term rental markets

As the rise of peer-to-peer markets are quite recent, the academic research literature is still segmented and premature with most of the articles published in the last few years. One of the first detailed overview of P2P Markets is provided by Einav, Farronato, and Levin (2016). They argue that the two most important features a P2P business is that it has to provide an efficient market mechanism with the ability to incorporate dispersed information, and to minimize all transaction costs and barriers for both the buyer and seller side. Due to this, P2P marketplaces have their highest raison d'être in segmentation and/or heterogeneity is a central problem, such as in ride-sharing and accommodations. Efficient market design, searching and pricing algorithms, and feedback mechanisms are also essential to provide a seamless supply of services and to overcome potential incentive problems. These markets can be either centralized (e.g. Uber) or decentralized (e.g. Amazon), but there are industries where both methods are in use (e.g. P2P loans). Einav, Farronato, and Levin (2016) argue that decentralization in the home-sharing industry is essential in order to provide a large set of options for individual customers. The authors also provide a theoretical model to measure the potential efficiency of P2P production, and show it should help to reduce price fluctuations due to the increased elasticity of short-term supply.

The previously mentioned model by Einav, Farronato, and Levin (2016) is fully in line with the findings of previous empirical research: Zervas, Proserpio, and Byers (2017) analysed the impact of Airbnb on the hotel industry in Texas with the following differences-in-differences specification (where X is a matrix of other variables, h_i are hotel fixed effects, and τ_t are time-varying revenue differences):

$$\log Hotel\ Rev_{ikt} = \beta \log Airbnb\ Supply_{kt} + X'_{ikt}\gamma + h_i + \tau_t + City_k * Month_t + \varepsilon_{ikt}$$

They estimated that a 10% increase in Airbnb supply results in a statistically significant 0.39% decrease in hotel room revenues. The overall causal impact of Airbnb is a 8-10% revenue decrease, affecting lower-priced hotels more (they face more direct competition in Airbnb). This effect is mainly due to the less aggressive hotel room pricing in peak seasons, when the demand is high. Jancsik, Michalkó, and Csernyik (2018) shows similar results in Budapest: utilization rates of hotels are unaffected by the recent rise of Airbnb offerings.

Another range of research is focusing on the less direct effects of Airbnb. Traditionally, the short-term rental and hospitality market, and the long-term rental and residential housing market had little cross-impacts between them. They have almost disjoint demand sets (tourists/business travellers vs. residents) and their supply side have been made up of different players. However, the later changed by the marketplace Airbnb is offering: property owners and managers can advertise apartments to a wider audience for a significantly smaller cost. As an increasing number of them decide to withdraw their offerings from the long-term rental market in order to list those properties on Airbnb, they create a connection between the above-mentioned markets on the supply side.

One effect this new relation may have is the effect on rental and housing prices. Barron, Kung, and Proserpio (2017) estimates the extent of this in the United States. Their model constitutes of a fixed stock of housing to be allocated in the long-term or short-term market. Landlords reallocate their housing units if the additional benefit of renting in the short-term market is higher than the additional costs of it. They take the introduction of a home-sharing platform as a cost reduction, and show that in theory, this raises rental prices. They also argue that house prices will increase more as the rise of the value of home ownership has two channels: it raises the rental prices but also enhances market options due to cost reduction. To test this, they run a regression with instrumental variables, and show that a 10% increase in Airbnb listings causes a 0.42% increase in rents and a 0.76% increase in house prices.

Merante and Horn (2017) estimate the effect of Airbnb on rents in Boston with a different approach: They measure the “density” of Airbnb listings ($\frac{sum\ of\ listings}{total\ housing\ units}$) in different census tracts and analyse the effects through a hedonic estimation with controls for the neighbourhood effect. They also estimate the impact of Airbnb listings on the long-term housing supply. Their results show that one standard deviation in Airbnb listings is associated with a 0.4% increase in rents. This means, that even back in 2016, there was already a city-wide effect of rent increases between 1.3-3.1%. They also find a significant negative correlation between Airbnb offering and housing supply, indicating that new listings are in fact reducing the housing supply in the town.

Sheppard, Udell, et al. (2018) focuses on more general influences on housing prices in New York, by taking the local economic impact of guests into account. They argue that Airbnb can have both a positive (rising neighbourhood quality) and a negative (externalities, such as noise, safety) influence on property values. They estimate property prices by $P = \frac{R(v,x)}{u}$, where R is a function depending on the welfare of residents and the annual rent paid, while u is the user cost of housing (including interest rates, taxes, risks, and costs). They provide a monocentric model to show that the rise of population increases rents everywhere, but more in the town centre. However, there are opposite forces as the rise of income and the increase in demand for space should decrease the rents in the downtown and increase them in the suburbs. A back-of-the-envelope calculation predicts a 17.7% increase in housing costs. Their hedonic empirical estimate shows that a doubling of Airbnb accommodations increases property values by 6-10% based on different setups. To test which parts of the towns are more affected, they perform a quasi-experimental estimation which puts the magnitude of this effect to 21-35%, significantly higher in commercial centre of the town.

As we have seen, there are some empirical estimations which suggests that home-sharing increases both rents and property prices. However, this impact, combined with the fact that Airbnb demand is usually very concentrated to the centre of the town[7] may lead to several side effects: affordable housing crisis, urban transformations and gentrification. Los Angeles's affordable housing crisis is documented by Lee (2016). He shows that a median household is already spending 47% of its income on housing, and 50% of the middle-income families and 90% of the low-income families are rent-burdened, meaning that they spend more than 30% of their monthly income on rents. He argues that only in a decade Airbnb have already had a major effect on this, as 143,000 'affordable' apartments have been converted into 'unaffordable'. He also shows that rents in the neighbourhoods with the highest share of Airbnb listings (Venice, Downtown, Hollywood etc.) are increasing 33% faster than citywide. Lee also shows evidence that Airbnb is correlated with gentrification in adjacent neighbourhoods and may intensify segregation and inequality.

The gentrification and urban transformation effect have been studied by Garcia-Ayllon (2018) as well, who performs geostatistical spatial analysis to measure the impacts of Airbnb in three of the most popular tourist destinations in Spain: Madrid, Barcelona and Palma de Mallorca. Garcia-Ayllon measures different static and dynamic Geographical Information Systems (GIS) indicators in different neighbourhoods across the three cities. These indices measure the intensity of both hotel and P2P accommodation offerings in districts, the price index of the rental market (both static indicators), the tourist pressure exerted on the city, the growth rate of the rental market, and the urban migration within the city (dynamic indicators). Analysis of the static indicators shows similar pattern in the cities: while (unsurprisingly) both hotel and Airbnb offerings are denser as we get closer to a specific (touristy) part of the town, Airbnb is even more centred into the middle of the town where prices are higher. Dynamic

[7] Check any city on https://www.airdna.co to make sure about this

indicators show evidence of greater increase in rental rates in Airbnb-focused districts and of more frequent changes of home ownership in central districts compared to the outer ones. These are all signs of an urban transformation where local residents move to the suburbs and downtown housing units are acquired in order to convert them to the short-term rental market. This, combined with the presence of spatial correlation between tourist and urban GIS indicators, shows evidence on Airbnb's contribution to the phenomenon of gentrification.

As it is clear now, in the recent few years there has been many efforts to document the direct, indirect and spillover effects of Airbnb and other home-sharing platforms. Focusing our point of view to the rental price variation effect, we have seen that there were some efforts to create theoretical models discovering the possible consequences of Airbnb. A common element in these models is that they usually relied on the reduction of entry cost barriers into the short-term rental market, and derived rental price increases from this phenomenon. However, when searching for empirical evidence, they all regressed (among other variables, fixed effect, etc.) price increases purely on Airbnb supply. In contrast to this, this paper applies the methods of Quigley and Raphael (2005), who show a relationship between the available housing stock supply and the rental price index, estimating a significant 0.358 price elasticity of supply in unregulated environments by regression.

1.2. Agent-based models and regression trees

A short introduction on agent-based modelling, based on Macal and North (2010): Agent-based modelling is a new 'ground-up' approach which spans across a broad range of disciplines. The key element of this modelling method is that it is composed of 'agents', small individual elements with heterogenous attributions, who interact with each other and/or the environment. These agents are uniquely identifiable and always have a state, which varies over time as they perform different actions. Some early applications of agent-based models can be found in predicting behaviour in the stock market and supply chains, measuring the spread of epidemics, and understanding consumer purchasing behaviour.

Classification and regression tree (CART) is a “binary recursive partitioning procedure capable of processing continuous and nominal attributes as targets and predictors” (Kumar (2009), pp. 181). The CART algorithm always partitions parent nodes (all elements in the beginning) into two subnodes across the attribute which provides the highest entropy (information gain) based on a splitting rule. The algorithm firstly results in a maximum-sized tree where no further splitting may be provided due to the lack of data. This tree is then pruned back to get the ‘honest’ tree based on evaluating the performance of each splitting in every pruning steps. Performing regression tree-based analysis has two main upsides: we can measure the importance of each attribute compared to each other, and we can derive predictions or estimations about a partitioned subset of data.

2. Data and methodology

In this chapter, the framework of the model presented to estimate the rent effect of home-sharing in Budapest is presented. This constitutes of three main blocks. The first one shows the model setup: Creates a map and the agents, which will be families in this setup, mirroring current conditions of Budapest. The second block generates all the varying parameters and handles the dynamic part of the model, including rent changes, movements, and housing units' conversion between owner-occupied, rented, vacant, and home-shared. The last part handles the data collection of the 2,000 runs, generating summary statistics and running regression trees on overall rent changes against the varying parameters.

2.1. Setup: creating the map and the agents

The model is running on a 200*200 map with 40,000 housing units, which is an approximately 1:20 scaling of Budapest's ca. 800,000 inhabited apartments.[8] This map has been broken down proportionally into 23 districts[9]. In order to have separate rent price estimations in each district, Each of them has been set up differentially, according to gathered data. The following parameters have been assigned to each district (a summary of these data is presented at Table 1):

- Square meters distribution: Apartment sizes in each district set up according to its distribution[10]. Since there are only categories of sizes, the model was simplified to have seven types of apartments: 25, 35, 45, 55, 70, 90, and 120 square meters
- Rental share: Share of long-term rental offerings out of all housing units[11]
- Airbnb share: Share of housing units currently listed on Airbnb[12]

[8] https://www.ksh.hu/nepszamlalas/tablak_lakasviszonyok 5.6
[9] https://icon.cat/util/elections/dWxRGbbIUU
[10] Based on https://www.ksh.hu/nepszamlalas/tablak_lakasviszonyok 5.6
[11] Based on https://www.ksh.hu/nepszamlalas/tablak_lakasviszonyok 5.3
[12] Based on https://www.airdna.co/vacation-rental-data/app/hu/default/budapest/overview

- Rental prices: Current average rental prices in districts[13], weighted by apartment size
- Commute time: Average expected travel time to the downtown[14]

After creating the map with all the housing, families that are not on the short-term rental market are assigned to all homes. This has been done by combining these two information sources: information about the average household size for all seven apartment size categories[15] and information about the relative share of households of different sizes[16]. Based on these two sources the share of family sizes in each unit types (see Table 2) was estimated and accordingly the families were assigned to map units

The setup of family income is done in the following way: Firstly, the average income by household sizes[17] was checked and corrected based on the difference between Budapest and the national average[18]. Also – since these data have been collected in 2017 –, the income was also adjusted (increased) by 20% based on the average income raise in the last 2 years [19] (A little less than the actual income surge as other benefits does not have the same pace of growth). I also differentiate rental and owner-occupied one-man households as data[20] show that people who rent alone are almost always workers, while owner-occupiers may include pensioners as well. To avoid households with extremely low income, each of them has been granted a fixed minimum wage (usually the net minimum wage) and an additional variable term, which is based on the family size and the district they are living (I assume people living downtown earn more than outsiders), using the following equation:

[13] Based on: https://index.hu/gazdasag/ingatlan/2019/05/21/7_-kal_dragultak_a_budapesti_alberletek/?fbclid=IwAR3GLHMsDGlo2Di8QIdcivpn5kwMAPuEr8Jl5_vwq8sQq64DPkL2DPLgQy4
[14] Based on the average of time using car and public transportation
[15] Using https://www.ksh.hu/nepszamlalas/tablak_lakasviszonyok 5.6 and 5.7
[16] https://www.ksh.hu/docs/hun/xstadat/xstadat_eves/i_zhc016c.html
[17] https://www.ksh.hu/docs/hun/xstadat/xstadat_eves/i_zhc016c.html?down=2035
[18] https://www.ksh.hu/docs/hun/xstadat/xstadat_eves/i_zhc014c.html
[19] https://www.ksh.hu/docs/hun/xstadat/xstadat_evkozi/e_qli030b.html
[20] https://www.ksh.hu/docs/hun/xstadat/xstadat_eves/i_zhc031c.html

$$income_{fam} = fixed\ minimum_{size(fam)} + beta(3{,}5) * x_{size(fam)} *$$

$$* \left(\frac{1}{2} + \frac{price\ of\ apartment}{average\ price}\right)$$

Where *fam* indicates families, and *size(fam)* indicates the number of people living in them. The variable term is generated with the help of a beta(3,5) distribution, due to its similar shape as the distribution of wages[21]. A summary of incomes is presented at Table 3.

2.2 The model: dynamic moving game

2.2.1. Parameters

In order to generate results with different setups (scenarios), parameters which affect the outcome of each run are needed. In this model, I use the following ones:

- Price elasticity: As the model determines rental price changes using the price elasticity, it is set differently in each run within a range approximated by Quigley and Raphael (2005)
- Taste effect: If too many people want to move out from a district, it is a sign that demand is decreasing, so therefore the price of rents should as well. Every district gets an extra price modification each turn based on whether the moveout rate is higher or smaller (and by how much) than the average, based on the following function:

$$\frac{\Delta(rent_d)}{rent_d} = \left(\frac{\sum_{i=1}^{23} vacancy\ rate_i}{23} - vacancy\ rate_d\right) * Taste\ effect$$

$\frac{\Delta(rent_d)}{rent_d}$ indicates the percentage change district *d* obtains, and $vacancy\ rate_d$ indicates the share of vacancies (=recent moveouts) of all available long-term rental units in the district.

[21] Based on: https://www.fizetesek.hu/partner/region/budapest

- Final Airbnb share: The simulations were running with different final Airbnb penetrations, which varies around the share of listings of major Western Europe and US cities
- Conversion from owner-occupied to (long-term) rental: As recent trends show[22] some housing units – previously owner-occupied –are converging to rental offerings; I include a parameter for that. This also represents that some 'vacant' homes may come to the market, which decreases the reduction of the housing supply
- Share of Airbnb conversions from rental homes: As not all the new Airbnb listings have to be converted from the long-term rental market, this parameter allows for owner-occupied → Airbnb conversions as well
- Moving power of paying too much rent: Paying a higher rent relative to income decreases affordability, therefore increases the chance of moving to another place. This moving chance in every turn (for every family) is modelled by $(\frac{rent}{income})^x$, where x is a varying parameter
- Base movement percentage: Share of families automatically moving in a turn as a 'base' fluctuation
- Slope of movement: Landlords do not necessarily adjust their rents instantaneously to 'market prices', but as market price rents increase, there is an increasing chance of adjustment (and therefore, moveouts), captured by this parameter.

As the corner stones of the model are the price elasticity and total Airbnb conversion, optimally, after the regression tree analysis, they will come out as the most impactful model drivers. As new rental offerings increase the rental supply market, it may be a forceful effect as well, and

[22] https://www.ksh.hu/docs/hun/xstadat/xstadat_eves/i_zhc019c.html?down=1300

the other – somewhat arbitrary – parameters should have a smaller effect. A summary of these parameters is presented in Table 4.

2.2.2. Model for rental price changes

After the generation of the above-mentioned run-specific parameters comes the moving algorithm itself. The model runs for twenty periods; one period captures a quarter, so the total estimated timeframe is five years. Based on the current growth of Airbnb listings in Budapest – which was 67% in the last two and a half years[23] – this seems a realistic timeframe to arrive at a 2.5%-4.5% total share of Airbnb listings from the current 1.23%. For the sake of simplicity, total growth per turn is constant, so all the share changes are distributed equally to turns.

The model firstly selects those families who leave their apartments and become active rent-seekers (making their housing unit vacant or converted to Airbnb). The following reasons are set into the model for a family to move:

- The home may be converted into an Airbnb (captured by share of Airbnb conversion)
- They may move out naturally or the landlord 'kicks' them out because they paid low rent (and the landlord lets it again at market price, estimated by the base movement share and slope of movement)
- Families leave because they pay too high rent, or their overall satisfaction is lower, than zero (moving power of rent + preference)
- Owner-occupied homes may switch to rental or Airbnb offerings (conversion to long-term rental + share of Airbnb conversion from owner-occupied)

[23] https://novekedes.hu/ingatlan/ennyivel-hajtotta-fel-a-fovarosi-alberletarakat-az-airbnb

After those families 'move out', the model gathers data on vacancy, housing stock decrease, and moving families both district-by-district and citywide and performs the market rental price changes based on the previously discussed effects (supply decrease and taste response). With the new rent prices, families start looking for new homes. Firstly, each of them check fifteen random vacancies and obtains a 'satisfaction rate' this way: They rate each unit according to the following preferences:

$$rating_{fam} = 0.5 * \left(1 - \min\left(\frac{rent_{fam}}{income_{fam}}, 1\right)\right)^2 + 0.2 * \left(1 - \frac{travel\ time_{fam}}{60}\right) +$$
$$+0.3 * f(size(fam)) - 0.1 * penalty$$

Where $f(size)$ is a function giving a rating of maximum 1 based on the family size and the size of the apartment (bigger families tolerate small apartments less than one-man households), and $penalty$ is 1 if the size of the new apartment would be smaller than the current one (otherwise 0) to reflect loss aversion. After rating the fifteen apartments, their overall market 'satisfaction' is simply the highest value of the fifteen grades. While this rating system seems somewhat arbitrary, I believe it reflects the main talking points and preferences of searching for a new apartment, and the rating system is balanced, as different family sizes have the same average 'satisfaction' rate.

Families get ordered by this grade, and the ones with the lowest figures leave the town (they move to the suburbs). The remainders are choosing apartments in a random order, according to the following rules: They start to search and move in to the first home which has a rating at least as high as their previously determined satisfaction rate. If there is no more places like this (happens to the last ones), they go for the best alternative out of the remaining apartments, and their actual happiness will be lower than expected (they will move out in the next turn with a higher probability).

After 20 rounds, the model stops and the following overall results are being saved: parameter levels, rental prices in districts, average price level in the city, and average commute time of renters (suburban families are calculated with 75 minutes of commute time). After the data save, a new iteration starts with different parameters.

3. Results

In this section, the results obtained from the 2000 simulations are analysed. Firstly, the general summary statistics are presented and matched to comparable results from the cited papers in Chapter 1. After this, the regression trees are analysed based on whether the overall results are truly driven by the variables highlighted earlier as the most important ones. Lastly, the data is narrowed to a subset which mirrors Airbnb penetration in Barcelona in order to make predictions for this situation

3.1. General results

Table 5 presents district-wide and overall results based on the simulations. At first, we can see that the predicted average total increase of rent prices in Budapest – due to home-sharing – is 3.21%, from around 2,280 HUF/sqm to 2,360 HUF/sqm. This means that the monthly rental price of a standard 65 sqm apartment could increase by more, than 5,000 HUF only due to the increase of home-sharing activity from the current levels. Besides this effect, the estimated mean commute time increases from 27.27 to 33.8 minutes for renters, meaning that a person who goes to downtown every workday will lose around 27 hours a year as there are fewer long-term rental offerings in the centre of the city.

Looking at the price increases district-by-district, we see that they are highly unequal. The most affected parts of the town – somewhat unsurprisingly – will be district V-VI-VII with a predicted 8.3-10.7% rental price increase. These are the major tourist destinations in the downtown area where home-sharing already converted a large amount of housing units to the short-term market, a trend only to be continued further. However, there is a second group of districts which have an above-average predicted effect: the cheapest suburban districts (XVI-XVII-XXII-XXIII) with a price increase of 3.8-6.3%. In the model, as rent prices increase tremendously in downtown, and significantly in other districts (decreasing housing affordability[24]), suburban places become more favourable, especially for low-income families. Therefore, the demand signal of the model will be high, driving up rent prices. This result shows similarities with Garcia-Ayllon's (2018) estimations, showing largest housing market activities in downtown and in the outermost districts.

Comparing these predictions to other estimations, the model is in line with previous literature on how the largest impact is on the areas of the major tourist targets (usually located downtown). As for the magnitude estimations[25]: Kung, and Proserpio (2017) predicts a 0.42% rent increase for every 10% increase in listings. As the average number of 10% increases in my model is 9-10, these estimations would predict a 3.8-4.3% increase, which is only a bit higher than my model predictions. Sheppard, Udell, et al. (2018) estimates that a doubling of Airbnb accommodations increases house prices by 6-10%. Based on this, the property values should increase by around 7.5-13% in Budapest. This is not directly comparable to my results (as I estimate rents), but if Kung, and Proserpio (2017) estimates the connection between rental and selling prices correctly, the rental price increase should be around 4-7%, which is higher than my prediction, but is of similar magnitude.

3.2. Regression tree

Running a regression tree in MatLab[26] using parameters as regressors and the city-wide price increase as the regressed variable (see Figure 1), we see that the first split is based on the final share of Airbnb listings, creating two quite different groups. When the final Airbnb share

[24] Matching average household income and rental prices data, we can see signs of a housing affordability crisis in Budapest as well, as the median rent/income ratio is somewhere around 35-40%. As this ratio has a non-linear effect on preferences (paying 50% of income on rents is not just twice as bad as paying 25%), rent increases have a larger negative effect on preferences in districts where this ratio was already high.
[25] Naturally, as the estimations were performed in different cities, the results are not directly comparable, but if my model would predict something totally different, it would raise some questions.
[26] I run the regression trees with a minimum leaf size of 100 when depicting the tree itself (so that the tree does not get messy), and with a minimum leaf size of 5 for predictor importance (to have a true picture of parameter weights). This change does not affect the higher parts of the tree at all.

is less, than 3.67%, the average predicted rent increase is only 2.32%, but if it is more, this figure jumps up to 4.36%. The next splitting rule in both nodes is about the price elasticity: If both Airbnb share and price elasticity is low (lower, than 0.332), rents only increase by 1.79%. Airbnb share being low but elasticity high, rents increase by 2.89%. If the Airbnb share is high, the elasticity limit value is 0.316: under this, rents change by 3.25%, otherwise the increase is 5.38%. Checking predictor importance estimates, we see that the three major model drivers are new rental offerings, total Airbnb share and price elasticity, and the other five parameters have a significantly smaller importance. This means that those parameters I estimated more arbitrarily does not influence the model significantly, thus does not undermine its predictive ability.

3.3. Barcelona setup

In this section, a hypothetical event is analysed: what happens if Airbnb penetration in Budapest becomes the same as it is in Barcelona? This comparison makes sense due to several reasons: First of all, Barcelona is similar in size as Budapest[27], and has a high owner-occupancy rate as well[28]. Secondly, Barcelona has a more developed short-term rental market as the growth of listings is not extremely high anymore (yearly average of listings was 22,200 in 2016, 24,700 in 2017, and 27,800 in 2018, representing ca. 10-15% annual growth[29]). Finally, there is an estimation of 4% rental price increases for Barcelona from Segú (2018), a number my estimation will be compared with.

As ca. 28,000 listings from ca. 800,000 housing units (including vacant homes) represent a 3.5% total share for the short-term market, I aggregate results from scenarios where this share

[27] Barcelona had 684,000 households in 2011, compared to the 787,000 in Budapest at the same time (https://www.idescat.cat/emex/?id=080193&lang=en#h1000000)

[28] 78.5% owner occupancy rate ten years ago (http://www.cadtm.org/Barcelona-Rental-Market-Is-Out-of), the same as Budapest in 2011 (https://www.ksh.hu/docs/hun/xstadat/xstadat_eves/i_zhc019c.html?down=1300)

[29] https://www.airdna.co/vacation-rental-data/app/es/barcelona/barcelona/overview

is between 3.4-3.6%. The results are the following: My model predicts a 4.05% increase in average rental prices from the current situation. This is not totally comparable without any reserves to Segú's (2018) result, as he estimated the impact from 0% to ca. 2.8%[30] in Airbnb listings share, while I estimate the effects from 1.23% (current situation) to 3.5%. However, the similarity of the results give ground to both my model predictions and the hypothesis that the rise of the short-term rental market has a significant effect on rental/housing prices.

3.4. Policies and recommendations

As the controversial side effects of the short-term rental market became more and more blatant, regulators faced problems all around the world dealing with Airbnb. Judgements varied in different states and countries, but as a general rule, most of the jurisdictions employed some kinds of limitations[31], e.g. to the maximum number of days per year a whole unit can be listed on Airbnb, setting it to 120[32]. However, the actual force of these regulations is questionable, as the market still grows exponentially, and the news are only about rare unique cases when prosecution and fines have been issued in cases of breached regulations.

The regulatory environment is not much simpler in Budapest. Generally, there are no limitations about the number of days a housing unit can be on the short-term market. Taxes – set by the government – are different, but not significantly higher[33] than letting the apartment out for residents, so it does not work as a deterrent force (even if we suppose that always all taxes are paid). Therefore, there are few tools in the hand of districts to limit the explosion of Airbnb listings (and prices). In the recent months, district VI and VII employed a one-time "parking allowance fee" of 1.5-2 million HUF to deter new listings, while district VIII set a

[30] The last data points he collected were from early 2017
[31] https://www.investopedia.com/articles/investing/083115/top-cities-where-airbnb-legal-or-illegal.asp
[32] https://www.cnbc.com/2018/12/12/los-angeles-passes-regulation-targeting-airbnb-rental-hosts.html
https://www.airbnbcitizen.com/regulation-change-january-2019/
[33] https://officina.hu/utazas-latnivalok/115-airbnb-adozas

yearly 1,820 HUF/sqm fee on housing units on Airbnb. It is too preliminary to measure the effects of these regulations, but early signs show that the growth of the short-term rental market will not decrease because of these.

In my opinion, the most important action would be to replace the converted units through new developments. This has been helped by the temporary VAT reduction in 2016 for housing developments, but as this legislation got revoked in 2018 (and as the labour supply dramatically dropped), development of new units will plunge: while there will be 14,600 new housing units in Budapest in 2019, only 5,900 will be constructed in 2020[34]. The development of new housing units where the demand is high should be incentivized. The financial support for these incentives could come from governmental taxes on short-term rental offerings: This way, landlords who profit from Airbnb would (at least partially) finance the development of new units. Another viable option could be one proposed by Lee (2016): We should initiate strict regulations on the listings of current housing units; however, slacken some of these for developers committing to building a large number of new properties.

[34] https://www.mnb.hu/letoltes/lakaspiaci-jelentes-2019-majus-hun-0508digi.pdf

4. Conclusions

In this thesis, I introduced a new approach to estimate the effect of the explosive growth of the short-term rental market on rental prices. I combined an agent-based model with an estimation method using the price elasticity of rental housing supply to predict district-wide and overall possible price increases in Budapest for the following years. Results suggest an overall 3.21% rent increase, which is distributed unevenly. Downtown tourist target districts may face an increase of 8-11%, and some suburban districts – where prices have been the lowest – also face higher rent increases.

The results of the model are generally in line with estimations from the current literature. Naturally, they are not directly comparable, but – as there are no current data on what city attributions amplify or shrink the effect of the short-term rental market – they are worth to be checked whether they are pointing to similar directions or not. The final prediction of possible rent increase shows very similar magnitude to the work of both Kung, and Proserpio (2017), Sheppard, Udell, et al. (2018), and Segú (2018), and the pattern of district-wide rent increases suggests a similarity with Garcia-Ayllon's (2018) work.

There are multiple possible extensions to this model: As the pricing and moving algorithm of the model is relatively simple, they could be improved and refined. Also, territorial preferences and other city-wide sophistications could be implemented (such as preference of Buda districts to the ones in Pest, etc.). With a revised pricing algorithm, the model might be able to handle both rental and selling price changes, extending the range of predictions.

Overall, this thesis gives an additional layer to the new and recently arising literature which tries to measure the effects and indirect consequences of the short-term rental market. This is a fresh, exciting but also very important topic, as regulators have not yet found an optimal way to tackle this phenomenon. My work – in line with the previous literature – shows that the effect is real, significant, and affects a large group of residents, so working towards an optimal solution maximizing the positive, but minimizing the negative effects is extremely important.

5. Appendix

District	Rental share (%)	Airbnb share (%)	Rental price (per sqm, 1,000 HUF)	Commute time (minutes)	Average sqm of housing units
I.	13.8	2.8	2.98	0	66.24
II.	6.2	0.6	2.21	30	78.26
III.	7.8	0.1	2.39	45	63.38
IV.	7.5	0	2.25	30	59.69
V.	16.4	13	3.14	0	68.39
VI.	14.3	9.6	2.92	0	62.04
VII.	15.4	9.7	2.57	0	56.71
VIII.	18.9	2.2	2.65	10	55.21
IX.	16.1	1.6	2.66	20	55.03
X.	11.2	0	2.30	40	55.23
XI.	6.8	0.3	2.56	35	62.87
XII.	7.8	0.4	2.29	35	72.52
XIII.	14.5	0.9	2.84	15	54.5
XIV.	7.7	0.2	2.34	35	57.9
XV.	7.2	0.1	2.04	55	62.93
XVI.	3.2	0.1	1.68	55	80.83
XVII.	3.1	0	1.45	60	81.03
XVIII.	4.8	0	1.78	60	72.57
XIX.	5.5	0.1	1.97	45	62.7
XX.	5.1	0.1	1.8	45	63.2
XXI.	6.5	0	1.89	45	64.11
XXII.	4.7	0.1	1.64	60	75.47
XXIII.	3.4	0	1.19	60	76.98
Average	**8.97**	**1.23**	**2.28**	**27.27**	**64.04**

Table 1: Summary of input data by districts

Housing unit size (sqm) / Family size	25	35	45	55	70	90	120	Average
1	58%	57%	49%	39%	30%	25%	13%	37.23%
2	30%	31%	33%	34%	34%	33%	32%	32.94%
3	9%	9%	12%	15%	16%	17%	17%	14.15%
4	3%	3%	5%	10%	15%	14%	19%	11.02%
5	0%	0%	1%	2%	4%	5%	12%	3.42%
6+	0%	0%	0%	0%	1%	2%	7%	1.24%

Table 2: Distribution of family sizes in each housing unit types

Income earned (1,000 HUF) / Family size	Minimum	Mean	Standard deviation
1 (renters)	99	320	100
1 (owner-occupied)	60	220	69.39
2	99	360	112.96
3	99	450	151.69
4	99	530	185.58
5	99	580	208.17
6+	99	580	208.17

Table 3: Statistics of family incomes

Parameter	Type of distribution	Minimum	Maximum
Price elasticity of rental supply changes	uniform	0.25	0.45
Taste effect	uniform	0.02	0.1
Final share of Airbnb-listed properties of all housing units	uniform	2.5%	4.5%
Conversion from owner-occupied apartments to rental	uniform	0%	3%
Share of Airbnb conversions to be made from long-term rentals	uniform	30%	70%
Moving power of high rents	uniform	5	10
Base (per turn) movement share	uniform	2.5%	7.5%
Movement slope	uniform	1	3

Table 4: Summary statistics of the dynamic model parameters

District	Final rent prices (per sqm, 1,000 HUF))	Rent price increase (per sqm, 1,000 HUF)	Rent price increase (%)
I.	3.08	0.1	3.28
II.	2.27	0.06	2.98
III.	2.44	0.05	1.98
IV.	2.3	0.05	2.29
V.	3.47	0.33	10.69
VI.	3.18	0.26	9.21
VII.	2.78	0.21	8.29
VIII.	2.71	0.06	2.16
IX.	2.72	0.06	1.98
X.	2.34	0.04	1.77
XI.	2.62	0.06	2.23
XII.	2.34	0.05	2
XIII.	2.89	0.05	1.73
XIV.	2.39	0.05	2.33
XV.	2.09	0.05	2.41
XVI.	1.77	0.09	5.46
XVII.	1.53	0.08	5.66
XVIII.	1.84	0.06	3.3
XIX.	2.03	0.06	3.19
XX.	1.87	0.07	3.54
XXI.	1.94	0.05	2.64
XXII.	1.7	0.06	3.81
XXIII.	1.26	0.07	6.29
Average	**2.36**	**0.08**	**3.21**

Table 5: General district-based and average results based on 2000 simulations

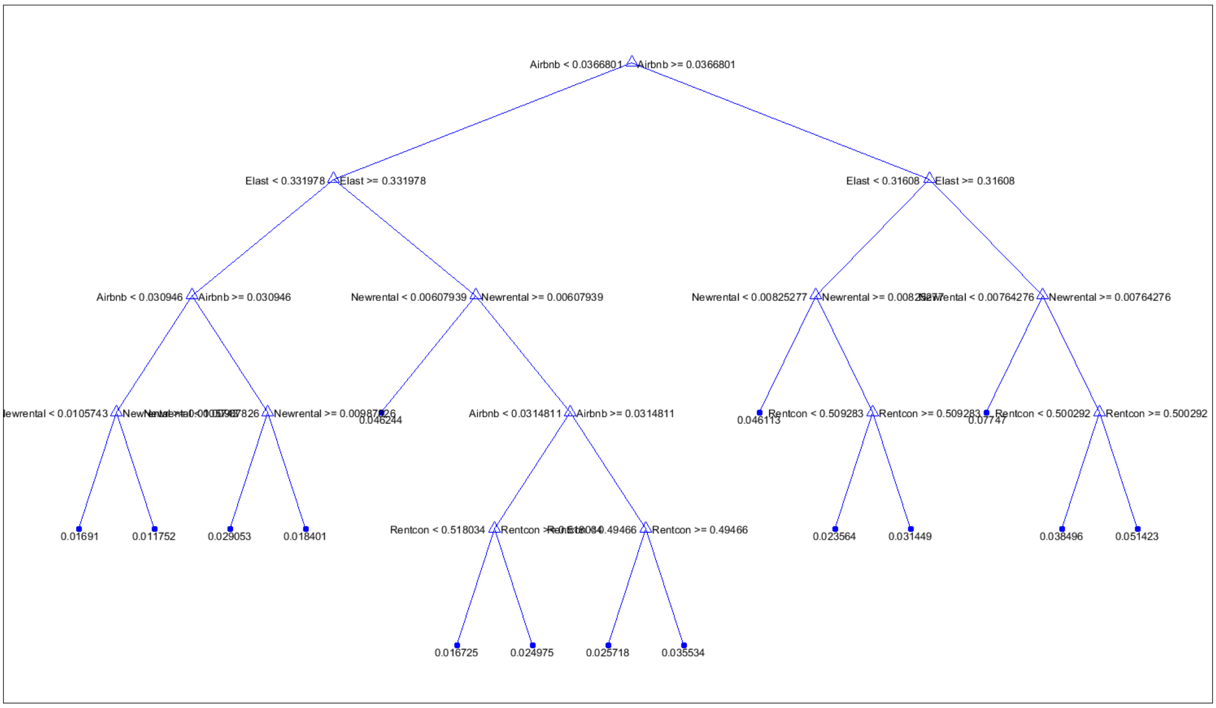

Figure 1: Regression tree on overall price increases with a minimum leaf size of 100

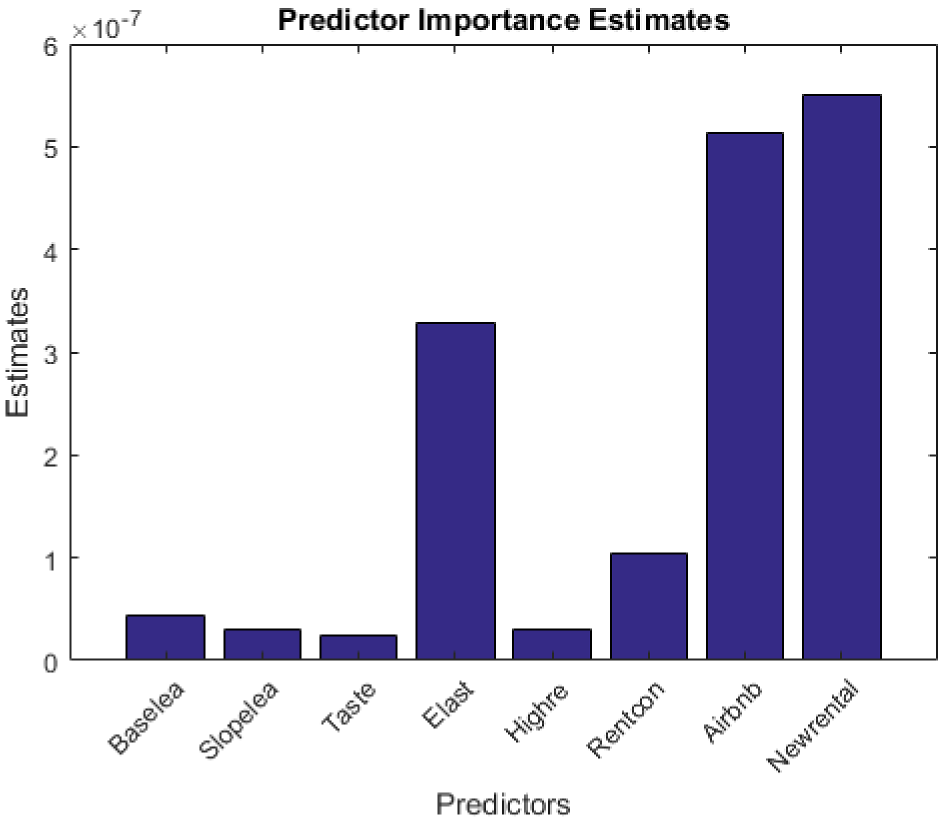

Figure 2: Predictor Importance Estimates when estimating overall price increases

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