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THE IMPACT OF SHORT-TERM RENTAL REGULATIONS

An Analysis of Airbnb Performance in Amsterdam following the Introduction of the 30-Day Policy

Supervisors:
Elisabetta Raguseo
Francesco Luigi Milone

Candidate:
Francesca Bottino

Acknowledgments

Before proceeding with the exposition of this paper, I would like to dedicate a few lines to all those who have been close to me in this journey of personal and academic growth.

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This thesis is the culmination of a chapter that has shaped me profoundly, and I dedicate it to all of you. Thank you for being part of this small piece of my story.

Abstract

The thesis analyzes the impact of short-term rental regulations in Amsterdam, focusing on the introduction of the 30-day annual limit for renting entire apartments through platforms such as Airbnb. Using a combination of descriptive statistics and regression models based on the Difference-in-Difference (DiD) approach, the study compares pre and post regulation trends to assess the effects on property availability, demand, and pricing. The analysis incorporates multiple regression models to control for various factors, including time-fixed effects and property-specific trends, allowing for a more nuanced understanding of the regulation's impact. Preliminary results indicate a significant reduction in listings and rentable days, along with an increase in revenue per night, particularly for properties directly affected by the regulation. These changes suggest a complex impact of the regulation, influenced not only by the policy itself but also by external factors such as the COVID-19 pandemic.

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1. Introduction

In recent years, the short-term rental market has grown exponentially, facilitated by digital platforms such as Airbnb, which have transformed both the tourism and real estate industries in many cities worldwide. While this growth has brought economic benefits, it has also raised concerns related to housing affordability and the sustainability of tourism in urban areas. In response, many cities across the globe have introduced regulations to limit the impact of such platforms on the availability of long-term housing and on the effects of over-tourism.

The study is set within a European context, focusing particularly on Amsterdam, a city known for having one of the most stringent regulatory frameworks. In 2019, Amsterdam introduced a 30-day annual limit on the rental of entire apartments. This policy was designed to address the shortage of housing for residents and manage the impact of mass tourism. However, the economic and social implications of this measure are complex and require careful analysis. Through the analysis of Airbnb data from 2017 to 2023, this thesis aims to quantify the effects of such regulation on Amsterdam's short-term rental market, focusing on changes in property availability, demand, and pricing.

The study builds upon a comprehensive literature review, which examines the rise of the sharing economy, the impacts of platforms like Airbnb on local communities, and the different regulatory frameworks adopted across various cities. Guided by this theoretical foundation, the research focuses on specific research questions and associated hypotheses that form the basis of the analysis. The questions aim to uncover both broader and more nuanced effects of the 30-day regulation on Amsterdam's short-term rental market, focusing on property availability, affected pricing strategies, and shifted demand patterns. The analysis begins with descriptive statistics to provide an overview of key trends, followed by a formal econometric analysis using the Difference-in-Difference (DiD) method.

2. Literature Review

This chapter starts by reviewing existing studies on the main topics discussed in this paper. It begins with an explanation of the Sharing Economy and how it has transformed the rental industry. This sets the stage for exploring the rise of Airbnb and other digital platforms that have taken advantage of the Sharing Economy. The paper then examines the socioeconomic effects these new business models have on local communities. Short-term rentals have changed the landscape, contributing to trends like "over-touristification" and the gentrification of certain city areas, which will be explained in more detail later on. Additionally, the study will address the growing need for regulations or standards to manage and control these types of rentals. An overview of the different regulations applied in some European and U.S. cities will be provided, along with their main impacts on communities and the rental market overall.

a. The Sharing Economy

The Sharing Economy is a socio-economic system that leverages technology to facilitate the exchange and sharing of goods and services between individuals or organizations. This model is primarily driven by the goal of utilizing underused resources more efficiently, which can lead to economic, social, and environmental benefits for all the stakeholders. (Haqqani, A. A. H., Elomri, A., & Kerbache, L., 2022).

The significance of the Sharing Economy in contemporary society lies in its potential to address inefficiencies in traditional market structures by connecting supply and demand on a large scale, promote resource optimization, and foster community engagement. By leveraging underutilized assets and promoting access over ownership and peer-to-peer interactions, the sharing economy promotes sustainability, affordability, and inclusivity, thereby challenging conventional notions of ownership and consumption.

The paradigm shift [1] has been supported by a significant transformation in consumer behavior: consumers are increasingly prioritizing experiences and convenience over the possession of goods. This transition has been greatly accelerated by technological advancements, particularly in mobile computing and the internet, which have lowered barriers to sharing and accessing goods and services on-demand. These technological platforms not only connect users but also build trust through rating systems and real-time interactions, further fueling the growth of the Sharing Economy.

Based on the relevance today, Sharing Economy is a challenger to long-established traditional economic models since it provides an alternative way of accessing services and goods (Möhlmann, 2015). Zhu and Liu (2020), summarize the views and definitions of multiple researchers on Sharing Economy by describing the model as a situation where firms or individuals with idle resources provide these resources to the community through a platform owned by a third party for a fee.

The representation of this model is based on three key players: the Owner, who offers an asset and receives a rental fee; the Seeker, who requests the asset and pays a fee; and the Platform, which facilitates transactions and charges a service fee. (Figure 1).

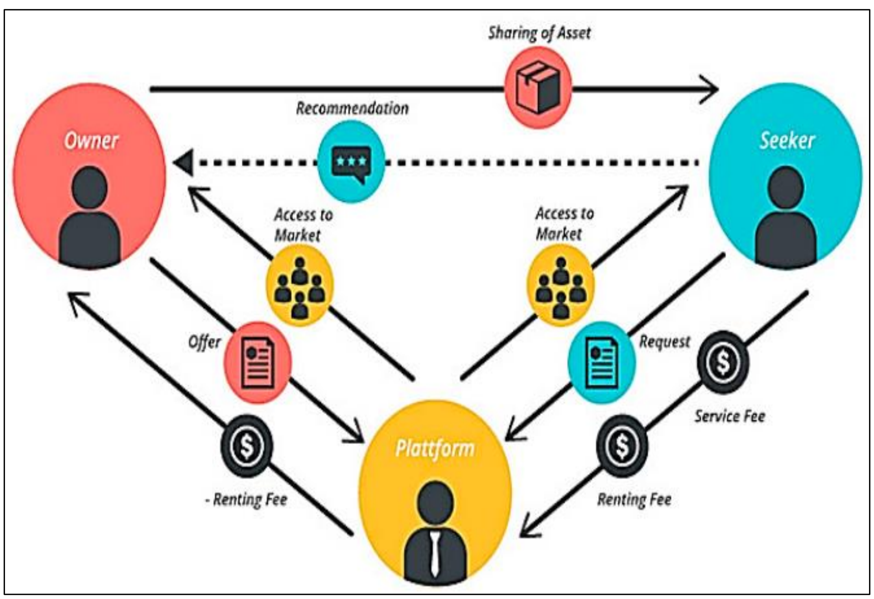

Figure 1: Basic visualization of a sharing economy model.

[1] A paradigm shift is an important change that happens when the usual way of thinking about or doing something is replaced by a new and different way (Merriam-Webster Dictionary, 2024).

As the digital age continues to reshape industries and redefine consumer behaviors, the sharing economy has emerged as a transformation force in the global marketplace. In 2022, Allied Market Research valued the market value of the Sharing Economy at $387 billion and projected that it would reach $827 billion by 2032. (Allied Market Research, 2023).

b. The rise of Airbnb

The transformative effect of sharing platforms extends across various industries, such as hospitality (e.g. Airbnb), transportation (e.g., Uber, Lyft), retail (e.g., Etsy, eBay) and even finance (e.g., peer-to-peer lending platforms). By embracing the power of technology and connectivity, these platforms have reshaped business models and democratized access to goods and services, empowering individuals to monetize their assets and participate in the Sharing Economy ecosystem.

One of the most significant manifestations in the hospitality sector is the rise of Airbnb, which is often described as a disruptive innovation due to its major changes to the industry. Founded in 2008, Airbnb pioneered the concept of peer-to-peer accommodation sharing, enabling individuals to rent out their homes to travelers in search of unique and authentic lodging experiences. The company was initially recognized as Unicorn, a term for privately held startups valued at least US $1 billion (Lee, 2013). In December 2020, Airbnb transitioned from a private to a public entity through an initial public offering and is now traded on the Nasdaq Stock Market with a market cap of approximately US $90-100 billion.

Researchers have identified several factors that drive customers to adopt Airbnb services, with low cost being a primary motivator. (Paulauskaite, 2017), (Guttentag, 2017). Airbnb offers guests a wide range of rental options, including entire places, private rooms, hotel rooms, and shared rooms, which can provide cost-saving options for solo travelers who opt for shared properties. In addition, group travelers can save money compared to traditional hotels. A recent NerdWallet analysis revealed that the average Airbnb rental for six people was 33% cheaper than booking three hotel rooms (NerdWallet, 2024). Additionally, numerous Airbnb listings offer fully equipped kitchens, which can help guests save money

on meals. The pursuit of an authentic local experience is another key motivator for many guests to choose Airbnb accommodations. Airbnb's "live like a local" approach offers guests the opportunity to stay in properties that are managed and designed by residents, resulting in unique and authentic experiences (Prayag, 2018). This enables guests to gain an unconventional understanding of the local culture and daily life in their destinations (Guttentag, 2017). Social interaction is also a significant aspect of the local experience, as Airbnb guests have the chance to interact with hosts, neighbors, and other guests, creating unforgettable experiences and social benefits. (Lee, 2018), (Ding, K., 2023).
Moreover, one of the main features of Airbnb is the possibility for both hosts and guests to make a review to each other after their stay, and this definitely helps to build trust and accountability inside the platform. Hosts can also set their own rental rates and availability, giving them greater control over how they use their space and how much income they earn. Airbnb has also been acclaimed for its ability to support local economies and their communities. Travellers are encouraged to stay in neighbourhoods and communities that may not have as many traditional hotels or accommodations, therefore Airbnb can help to bring tourism and economic activity to new areas.

Airbnb's disruptive innovation model not only challenges the dominance of traditional hotel chains and revolutionizes the way people travel and experience destinations, but also impacts communities, hosts, guests, citizens, and customers.

c. Impact on local communities

Many articles in the literature discuss the effects that sharing economy platforms have on local communities, and this study aims to provide a clear and broad overview of these impacts. After reviewing a large number of articles, the impacts were grouped into the following categories.

- Impact on housing prices and rents.
- Impact on the hospitality industry, examining the effect on hotels.

- Impact on society, local dynamics, and culture.
- Impact on sustainability: main negative impacts on ecological preservation of cities.

In the following paragraphs, the articles found for each of the four points listed above will be analysed in more detail.

i. Impact on the housing prices and rent

Firstly, Airbnb emerged to address inefficiencies in rentals, such as vacant apartments during holidays, which align well with short-term rentals. However, if homeowners utilize home-sharing platforms to permanently transit from long-term to short-term rentals catering to tourists, the availability of units in the long-term rental market diminishes, resulting in heightened housing prices and rents.

Numerous studies have examined the impact of short-term rentals on housing prices, employing both quantitative and qualitative analytical approaches. For instance, Garcia-Lopez et al. (2020) conducted a study on the housing market in Barcelona, finding that Airbnb has led to increases in both rents and prices. The paper specifies that a neighbourhood with 54 additional active listings (about the average level in 2016) experiences a 1.9% increase in rents, with transaction and posted prices rising by 4.6% and 3.7%, respectively. Moreover, in the most touristy areas of the city, an increase of 200 listings (the average number in the top decile of Airbnb activity distribution in 2016) results in a 7% rise in rents and a 17% and 14% increase in transaction and posted prices, respectively.[2]

Another example is the article of Franco et al. (2021), which quantifies the impact of Airbnb short-term rentals on housing accessibility in Portugal cities. The article shows how, on average, a 1 percentage point increase in a municipality's Airbnb share translates into a 3.7 percent increase in housing prices. Moreover, exploring the spatial heterogeneity of Airbnb's impact within the cities of Lisbon and Porto, it has been found strong localized effects in

[2] In this study, the rental price refers to the cost that tenants pay to rent a property, the transaction price refers to the actual price at which the properties are sold, and the posted price refers to the asking price properties are listed for sale.

historic centers and areas attractive to tourists. Compared to a low-tourist district, house prices in a high-tourist district increased by 24.3 percent in 2015 and 32.3 percent in the first quarter of 2016, relative to the pre-Airbnb expansion period (pre-2014).

Despite being a recent phenomenon, research papers already exist estimating the effect of Airbnb on housing markets also in the United States. Barron et al. (2020) and Koster et al. (2020) are notable examples. Barron et al. (2020) examine the impact of Airbnb on rents and house prices across all US cities. Using a 'shift-share' instrument, they find that a 1% increase in Airbnb listings raises rents by 0.018% and housing prices by 0.026%. At the same time, Koster et al. (2020) analyses the effects of Airbnb bans implemented by some local governments in the Los Angeles area and discovers that banning Airbnb could lead to a decrease in prices of about 5%.

The short-term rental sector may seem insubstantial compared with the housing market as a whole. For instance, Airbnb supply in New York City (NYC) was highest in 2019, with approximately 50,000 listings available. According to the U.S. Census Bureau, over 2 million housing units were occupied by tenants in the same period (U.S. Census Bureau, 2019), meaning that <3% of the housing supply in the city was dedicated to Airbnb. Nevertheless, researchers have addressed that the economic impact of Airbnb could be much greater than its share in the housing market. Researchers estimate that renters in NYC suffer an increase in housing prices (Sheppard & Udell, 2016). In particular, using a hedonic model estimate[3], a doubling of Airbnb listings is associated with increases of 6% to 11% in house values.

Another article analyzing the effects of short-term rentals focuses on Amsterdam and Barcelona, examining how Airbnb influences both rental prices and residential stability. Residential stability, measured by the average length of time residents

[3] A hedonic model estimate is a type of regression analysis used to determine the impact of various factors on the price of a good or service, typically real estate. The term "hedonic" comes from the idea that the value of a good is derived from the characteristics or attributes it possesses (Zakaria, F., & Fatine, F. A., 2021).

remain in their homes, was found to decrease in both cities as Airbnb listings increased. In Amsterdam, this pressure is largely due to rising rent prices, which makes housing less affordable for long-term residents. By contrast, in Barcelona, the increase in property values has a more direct impact on residential stability, reflecting the city's higher rate of homeownership. This illustrates how short-term rentals can drive housing market pressures differently depending on local housing structure (Valente et al., 2023).

In conclusion, the widespread adoption of Airbnb has worsened the rise in housing prices and rents, particularly in tourism-intensive areas, as evidenced by various studies conducted globally. However, the correlation between Airbnb's presence and rental growth prices invites further examination to understand the complex interaction of causality (Schäfer et al., 2016). Is Airbnb's presence that intensifies rises in rent prices? Or Airbnb listings are located where rental growth is naturally high?

ii. Impact on the Hospitality industry

The impact of Airbnb on traditional hotels is a research topic of great interest to industry professionals and academics. Dogru et al. (2020) expanded the scope of research to a global context, analyzing Airbnb's effect in four international cities: London, Paris, Tokyo, and Sydney within the period 2008-2017. To measure the degree of Airbnb's influence on the principal hotel markets, three key performance metrics were selected:

1. RevPAR (Revenue per Available Room),
2. ADR (Average Daily Rate),
3. OCC (Occupancy Rate).

For each city, an ordinary least square (OLS)[4] regression model was built, and the results were consistent across all markets. The findings indicate that the impact of Airbnb on hotel revenue per available room (RevPAR) and occupancy (OCC) rates is both negative and statistically significant. Specifically, a 1% increase in the number of Airbnb listings corresponds to a decrease in hotel RevPAR of up to 0.031% and a decrease in hotel OCC of 0.016%. The effect on ADR was less significant, with a related decrease of only 0.001%. (Table 1, 2, 3 in the Appendix A).

In a broader analysis, Yang et al. (2021) synthesized 466 evaluations from 33 different studies on the topic, confirming a moderate negative effect of Airbnb listings on hotel performance with some variability depending on the city analyzed. The study's meta-regression analysis[5] reports that the negative impact is smaller for high-end hotels than for low-end hotels and decreases over time. In addition, this effect is less pronounced for European hotels than for Asian hotels.

The impact of Airbnb wasn't just studied in terms of how it affects hotel performance; researchers also tried to figure out how many customers Airbnb is taking away from the hotel market. The study by Guttentag et al. (2017) aimed to evaluate the market share Airbnb has captured from traditional hotels, exploring the demographic profiles of customers who prefer Airbnb, the factors influencing their choice, and any correlations with specific hotel categories or customer preferences.

Key insights emerged from a representative survey of nearly 900 respondents:

- A predominant 64.8% of respondents selected Airbnb as an alternative to traditional hotels, especially favoring it over mid-range options, while upscale hotels were least likely to be substituted. Only a minor fraction (2.3%) used Airbnb for trips they otherwise would not have undertaken.

[4] OLS is a type of linear least squares method used to estimate the unknown parameters in a linear regression model. The least squares method works by minimizing the sum of the squares of the differences between the observed values of the dependent variable and the values predicted by the linear function of the independent variables.

[5] Meta-regression analysis is a statistical technique used within meta-analysis to explore how study-level characteristics influence the effect sizes reported in multiple studies addressing a similar research question.

- The choice to use Airbnb generally did not affect the length of stays, with 72.7% reporting no change. However, 26.5% of the users extended their stays due to the flexibility Airbnb offers.
- The analysis also found demographic trends in substitution preferences: younger respondents tended to replace hostel stays with Airbnb, whereas older individuals preferred it over bed-and-breakfast options. Further distinctions were observed between travelers with children and those identified as backpackers, both of which showed the likelihood of choosing alternative accommodations.

Airbnb's effects go beyond just the hotel industry, impacting the housing market and regulations, as pointed out by Ram et al. (2021). While Airbnb helps meet seasonal demand for accommodations, it also creates challenges in following regulations and ensuring fairness.

Moreover, its influence on tourism activities highlights Airbnb's significant impact on the entire tourism industry.

iii. Impact on the Society and Culture

Airbnb impacts various aspects that influence the social and culture sphere of a local community, some of which are positive while others raise concerns.

On the positive side, Airbnb has emphasized the renewal and economic revitalization of previously neglected neighborhoods, fostering the growth of local businesses and job creation in the hospitality and service sectors. However, this revitalization often comes with the gentrification phenomenon[6], driven by an influx of tourists, which can change the character of these areas – sometimes benefiting the local community but also potentially causing harm.

Numerous studies have analyzed the impact of gentrification on local communities. The process is usually influenced by global economic factors, high demand from overseas

[6] Gentrification is the process of change in the character of a neighborhood through the influx of more affluent residents (the "gentry") and investment (Finio, Nicholas; 2022).

elites, and local developments, such as universities, which can increase property values and displace long-standing residents. Although Airbnb acts as a catalyst for what is known as "tourism gentrification," converting long-term rentals into short-term accommodations and reducing housing availability, it is not always the initial cause of changes, as evidenced by areas like Dublin where gentrification predated Airbnb's popularity, but it surely impacts the society and culture of a local community. (Rabiei-Dastjerdi et al., 2022).

On the negative side, critics of home-sharing platforms point out that short-term rentals can disrupt residential areas with negative externalities of guests such as noise, uncivil behavior, and displacement of long-term residents. Safety concerns have also emerged, including incidents of vandalism and other criminal activities in properties listed on Airbnb. Additionally, issues such as increased parking, waste management challenges, and noise pollution have been exacerbated, leading to deteriorations in residents' quality of life. Observations from Schäfer and Braun (2016, p. 305) specifically highlight the increase in "*more trash, more noise, and more open-air parties*" as significant inconveniences brought about by Airbnb in neighborhoods.

Additionally, the phenomenon of “over-touristification[7]”, driven by the proliferation of short-term rentals, can lead to a sense of alienation among long-time residents and even displacement from their neighborhoods as housing prices rise due to increased demand from tourists.

Heritage sites may also lose some of their authenticity due to rapid transformations aimed at accommodating visitors. For instance, significant changes in the character of neighborhoods or the creation of facilities that attract induced tourism, such as bars and restaurants, can alter the original essence of these sites.

Moreover, Airbnb has faced criticism for potential racial discrimination, particularly highlighted by the *#AirbnbWhileBlack* movement. Black travelers shared their experiences

[7] Over-touristification is the excessive transformation of a place due to overwhelming tourist activity, leading to overcrowding, strain on local resources, and negative impacts on residents and the environment (Bugalski, Łukasz, 2023).

of booking rejections, often believing their race played a role, and found higher success when modifying profile names or photos. A 2017 Harvard study found that guests with African-American-sounding names were 16% less likely to have their booking requests accepted compared to those with white-sounding name (Edelman, B. G., & Luca, M., 2014). In response, Airbnb introduced the *Instant Book* feature, which allows guests to book accommodations immediately without prior approval from the host, reducing the opportunity for racial bias in the booking process.

iv. Impact on Sustainability

Today the sustainability sphere plays a crucial role in our society, and it is essential to consider the environmental Airbnb's impact on local communities combined with all the others that have been mentioned above.

In a study performed by Caldicott et al. (2020), a Triple Bottom Line three-pillar analysis of Airbnb's positive and negative impacts was conducted. This framework created by Elkington, aims to include the environmental and social dimensions in the traditional measures of accounting profit. It incorporates three dimensions of performance: Environmental, Social, and Financial, and it considers them all with the same weight. The study, based on 25 research articles, analyzed Airbnb's economic viability, social well-being, and the ecological preservation of the territory.

Since the economic and social impacts have already been covered, in this paragraph the focus will be on the environmental perspective. The review demonstrates a void in research discussing the relationship between Airbnb and natural environmental aspects of sustainability because positive aspects that Airbnb brings to the natural environment were not raised at all, while negative ones such as noise, waste management, security, fire, and safety, were narrated in only one of the 25 studies reviewed.

The research conducted by Gurran & Phibbs (2017) investigated the main problems associated to short term rentals within the ecological preservation of the local territory. Below are presented the main key challenges exposed.

- Lack of awareness and compliance with local regulations: Visitors renting short-term rentals may not be familiar with local policies and rules, leading to improper waste management, disregard for fire safety protocols, and other violations.
- Noise pollution: One of the most significant concerns is noise disturbance caused by parties or gatherings in short-term rentals, which can be a nuisance for residents.
- Increased traffic and parking congestion: The influx of visitors staying in short-term rentals can contribute to traffic congestion and competition for limited parking spaces in certain areas.
- Overreliance on ride-sharing services: The availability of short-term rentals may encourage visitors to rely more heavily on ride-sharing services like taxis or Uber but especially on delivery services like Glovo, UberEats, potentially increasing emissions and traffic.

These issues underscore the importance of developing appropriate regulations and guidelines to mitigate the negative environmental impacts of short-term rentals and promote sustainable tourism practices within local communities. Notably, issues such as noise pollution, inadequate waste management, and non-compliance with local safety protocols underscore the need for better regulatory frameworks and enhanced community engagement strategies. These findings focus on a critical gap in research — particularly in the potential positive impacts of such rentals — which suggests an interesting area for future studies. Addressing these sustainability challenges is essential not only for improving local community experiences but also for ensuring the long-term viability of short-term rental platforms in harmony with ecological preservation goals. Moving forward, stakeholders must collaborate to forge pathways that align more closely with sustainable development principles, thereby ensuring that short-term rentals contribute positively to the communities they affect.

d. The need for regulations

As it has been described, short-term rentals like Airbnb have various impacts on local communities, many of which are negative. Over the last decade, the need to manage and control these rentals has become evident. This has led to the implementation of local policies aimed at curbing the adverse effects of overtourism and related nuisances by establishing limits and regulations around temporary stays.

Some of the key motivations for introducing these regulations include the risk of illegal subletting of rented apartments to tourists (Llop, 2017) and ensuring fair competition. Appropriate regulatory prescriptions are necessary to maintain a competitive and stable market, impose minimum safety standards, and define spatial restrictions (Dell et al. 2017). Urban planners and policymakers in municipalities are required to implement and assess the effectiveness of local planning controls because they are crucial for managing neighborhood nuisances, traffic congestion, and parking issues, as well as for safeguarding the availability of permanent rental housing. It is essential to differentiate between various types of short-term Airbnb accommodation listings and understand their potential impacts on neighborhoods and housing markets (Gurran & Phibbs, 2017).

This widespread adoption of regulatory measures by cities around the world indicates a recognition that the burgeoning trend of short-term rentals must be supported by a robust policy framework. Numerous studies have called on governments to take an active role in crafting suitable policies to regulate all forms of the sharing economy, including Airbnb. This is crucial to ensure that society benefits from these platforms without losing control over the accommodation sector (Fang et al. 2016; Schäfer & Braun 2016).

Despite the evident need for those regulations, local governments worldwide are still struggling to regulate peer-to-peer (P2P) platform facilitating short-term rentals such as Airbnb in response to concerns raised particularly around their negative externalities (Nieuwland & van Melik, 2018). The effectiveness of these regulations heavily depends on the specific context of each city, as successful enforcement requires commitment, decisiveness, and effective action from all involved stakeholders. The topic remains a focus of ongoing research, aiming to fully understand the implications for local neighborhoods and housing markets.

e. Overview of regulations across European and US cities

Cities around the world have implemented different policies to regulate the expansion of short-term rental platforms such as Airbnb, uniquely addressing local issues.
In Europe, the regulatory landscape varies significantly. Early adopters such as Amsterdam, London, Berlin, and Barcelona have influenced others, creating a patchwork of heavily regulated cities alongside those with more permissive or yet-to-be-regulated environments. The sample size is sufficient to explore various approaches, given that there is no consolidated or uniform method, and regulatory interventions must consider local factors. The underlying challenge everywhere remains balancing the benefits of the sharing economy while safeguarding community well-being and housing affordability.
Major cities including Barcelona, Berlin, Paris, San Francisco, and Los Angeles have implemented licensing requirements to ensure that hosts meet local safety and compliance standards, helping to maintain the stock of available housing. Additionally, to manage the impact on local housing markets, cities like Amsterdam, New York, Paris, and San Francisco have set limits on the number of days a property can be rented annually. Financially, Amsterdam and San Francisco have introduced taxes on rental income from short-term rentals to support municipal services and infrastructure improvements. In more stringent responses, Berlin and New York have enacted bans under certain conditions to protect residential spaces and ensure compliance with housing codes.

According to Von Briel, D., & Dolničar, S. (2021) in their study on "The evolution of Airbnb regulation – An international longitudinal investigation 2008–2020," cities are categorized based on their regulatory approaches into two main groups: 'end-run' and 'gap' cities. 'End-run' cities like San Francisco and Hobart had strict short-term accommodation regulations in place before peer-to-peer accommodation became widespread. Over time, these cities adapted their laws, shifting from stringent regulations to more flexible alternatives due to various stakeholder pressures. 'Gap' cities, like Amsterdam or Paris, lacked initial specific legislation for peer-to-peer accommodations, prompting swift development of new policies tailored to emerging challenges.

In the table below major cities have been classified based on the different kind of regulations they have enforced during the years (Figure 2).

City	San Francisco	New York	Amsterdam	London	Berlin	Paris	Barcelona	Reykjavik	Vienna	Hobart	Tokyo
Prior dates	*End-run*	*Gap*	*Gap*	*End-run*	*Gap*	*Gap*	*Gap*	*End-run*	*End-run*	*End-run*	*End-run*
2008	Activities start	Activities start	Activities start								
2009				Activities start							
2010		Strict Regulations									
2011		Regulation & Taxes			Activities start						
2012						Activities start	Activities Start Registration	Activities start	Activities start	Activities start	Activities start
2013			Strict Regulations								
2014	Regulation & Taxes		Collaboration Regul. & Taxes	Regulation & Taxes	Strict Regulations	Regulation & Taxes	Strict Regulations				
2015	Registration		Registration	Registration*		Collaboration	Regulation & Taxes			Regulation & Taxes	
2016	Refinement	Refinement	Refinement		Registration		Refinement	Regulation & Taxes	Regul. & Taxes Registration		
2017	Collaboration		Collaboration	Collaboration			Refinement	Registration		Registration*	
2018		Collaboration	Refinement		Refinement	Registration*	Collaboration	Refinement	Refinement		Registration
2019	Refinement	Refinement	Refinement			Refinement	Refinement			Collaboration	Collaboration
2020			Refinement			Collaboration Refinement	Refinement		Refinement		Refinement

Figure 2. Comparative evolution of Airbnb regulations.

The graphic shows that most cities began to see short-term rental activities around 2008 to 2012, during a phase where there were no significant regulations in place. Between 2010 and 2014, many cities started to introduce various forms of regulation to address the challenges posed by platforms like Airbnb. These regulations included strict rules in some cities, such as San Francisco and Berlin, as well as registration requirements in places like Barcelona and Amsterdam, along with the introduction of taxes in cities like San Francisco and New York. From 2015 onwards, several cities transitioned towards collaborating with short-term rental platforms and refining their regulatory frameworks. This period marked a shift towards finding a balance between the benefits of these platforms and the need to protect local housing markets and community well-being.

The study further deep dive into the level of strictness of different regulations. Using theoretical frameworks and legal theories that explains how the new business innovations can disrupt existing policies (Biber *et al.*, 2017), the authors rated regulatory strictness for all cities during the years 2008-2020 to observe the evolution of the regulations. In the figures below are presented the results based on a qualitative scale from 1 to 10. The lower value represents an unregulated city while the higher is a city with extremely restrictive regulations (Figure 3, 4). The evidence shows clearly that stricter regulated cities (end-run) lowered the strictness level over time while cities where the regulations were implemented after (gap) increased their level of strictness.

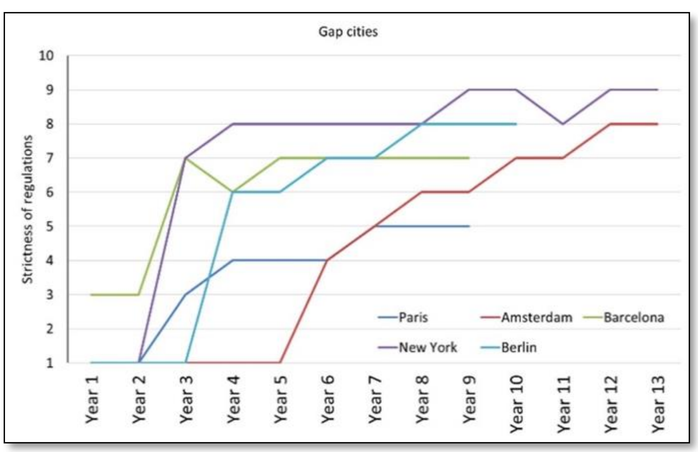

Figure 3. Strictness of regulation in different gap cities.

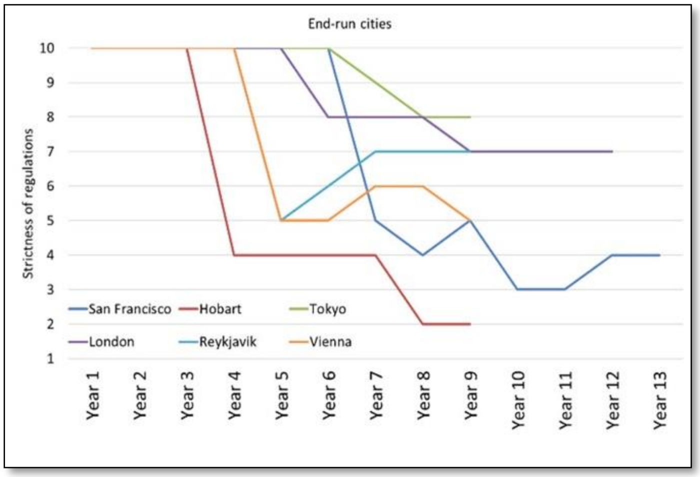

Figure 4. Strictness of regulation in different end-run cities.

Furthermore, cities are divided into four regulatory types: liberal, moderate, moderate-collaborative, and protective.

- Liberal cities, exemplified by San Francisco and Hobart, ultimately implemented generous regulatory frameworks after extensive debates among local stakeholders.
- Moderate cities like Paris and Vienna take a cautious approach, observing market impacts before legislating.
- Moderate-collaborative cities such as Amsterdam and Barcelona proactively engage with platform facilitators from the onset, integrating them into local tourism planning processes.
- Protective cities, including Tokyo, London, and New York, impose strict limitations on short-term rentals, with infrequent revisions to their regulations.

The classification provided by Von Briel, D., & Dolničar, S. (2021) is not the only approach to identify the different ways of regulating short term rentals. Other categorizations include the study of the objectives and limitations of short-term rentals (STRs) that lead to a specific instrument of regulation. According to Hübscher, M., & Kallert, T. (2022), the typical instruments can be divided into complete ban, quantitative, qualitative and spatial restrictions, as illustrated in the table below (Figure 5).

Instruments	Objectives	Limitations	Sources
Complete ban	Eliminate Airbnb-listings from a city or a certain neighborhood	Loss of positive effects of STR, taxes etc.	Nieuwland and Van Melik (2018) p. 816; Jefferson-Jones (2015, p. 564)
Quantitative regulations			
Limit the number of days or max. Guest numbers or max. Number of rentings	Protect the availability of housing units for long-term rentals	Monitoring necessary, but costly	Guttentag (2015, p 0.9); Oskam and Boswijk (2016, p. 30); Frenken and Schor (2019, p. 131)
Limit the amount of entire dwellings, but permit individual bedroom	Protect the availability of housing units for long-term rentals	Monitoring necessary, but costly	Martínez Nadal (2019, p. 43); Oskam and Boswijk (2016, p. 30); Frenken and Schor (2019, p. 131)
Taxation	Participate from the benefits; reduce the number of listings; level playing field in hospitality industry	No precise instrument to manage to impact of STR	Guttentag (2015, p. 10); Kagermeier *et al*. (2015, p. 15)
Spatial restrictions			
Limit the number of STRs per multi-family house; permission of owner associations	Find balance, integrate local owners	Monitoring necessary, but costly	Martínez Nadal (2019, p. 44); Frenken and Schor (2019, p. 131)
Relative proportion between regular flats and Airbnb listings in a neighbourhood	Contributes to the legal differentiation between private and commercial offers	Monitoring necessary, but costly	Jefferson-Jones (2015, p. 565); Frenken and Schor (2019, p. 131)
Spatial distance between two Airbnb listings	Might prevent additional entrants into the Airbnb market	Monitoring necessary, but costly	Jefferson-Jones (2015, p. 565)
Qualitative restrictions			
Qualify the listings, e.g. hygiene and security standards	Customer protection, level playing field in hospitality industry	Monitoring necessary, but costly	Jefferson-Jones (2015, p. 565); Kagermeier *et al*. (2015, p. 15)
Licensing/registration numbers	Increase the cost for the process; monitoring for city administrations	Time and effort for administration	Martínez Nadal (2019, p. 1); Jefferson-Jones (2015, p. 564)

Figure 5. Selection of typical instruments, and their objectives and limitations.

The study continues with an overview of the major European cities' restrictions over time which aligns with the previous study. One notable distinction lies in the fines imposed, which are determined locally and vary significantly across different jurisdictions.

In conclusion, despite the multiple regulatory approaches, from liberal to protective, and the variety of instruments used to address the impact of short-term rentals on housing markets and local communities as described in this chapter, the regulatory landscape remains complex, and it changes continuously. The ongoing adaptation of regulations highlights the dynamic nature of this issue, as cities strive to balance the benefits of the sharing economy with the need to protect housing affordability, community well-being, and the local economy.

3. Research Study

This chapter outlines the scope of the research, the focus of this dissertation, and the hypotheses under investigation. Following an overview of the topic through the literature review, the chapter discusses the rationale behind the selection of Amsterdam as the case study, the city's evolving regulatory framework, and the specific regulation chosen for analysis. Additionally, it presents the research questions that this thesis aims to develop and explore.

a. The choice of Amsterdam

After reviewing several regulatory strategies for short-term rentals implemented by governments, this study focuses on a specific city, Amsterdam, to determine the impacts of these regulations over time and provide a deep-dive analysis supported by Airbnb data. Regulatory responses are inherently local, needing to account for specific circumstances and challenges at each destination. In order to understand the different regulations and the impact related to the local context, as well as causes and effects, it is necessary to briefly summarize the specificity of the given city.

Amsterdam, a prominent tourist destination and an early adopter of Airbnb in Europe, provides a compelling case due to its proactive and evolving regulations aimed at balancing economic benefits while mitigating negative externalities.

Relevant statistics about the city of Amsterdam highlight its unique housing and tourism dynamics. As of 2023, Amsterdam's population was approximately 880,000 (Rentumo, 2024). The city remains a popular destination for international travellers, attracting millions of tourists each year, a number that has steadily increased over time – a part from the pandemic years – and reached almost 7 million of tourists in 2023 (Amsterdam Tourism Statistics, 2023). Reflecting this popularity, the number of Airbnb listings in the city was around 9,000 as of June 2024 (Inside Airbnb, 2024).

Amsterdam's housing market is characterized by a relatively low homeownership rate, with only about 29% of residents owning their homes (Valente et al., 2023). This is largely due to the high demand for rental properties, driven by the city's demographics, which include a significant proportion of young professionals and international residents. More than 30% of Amsterdam's housing stock is privately rented, a number that surpasses all the other main national cities. This sector has experienced notable growth, fuelled by rising housing costs and the influx of expatriates (Figure 6).

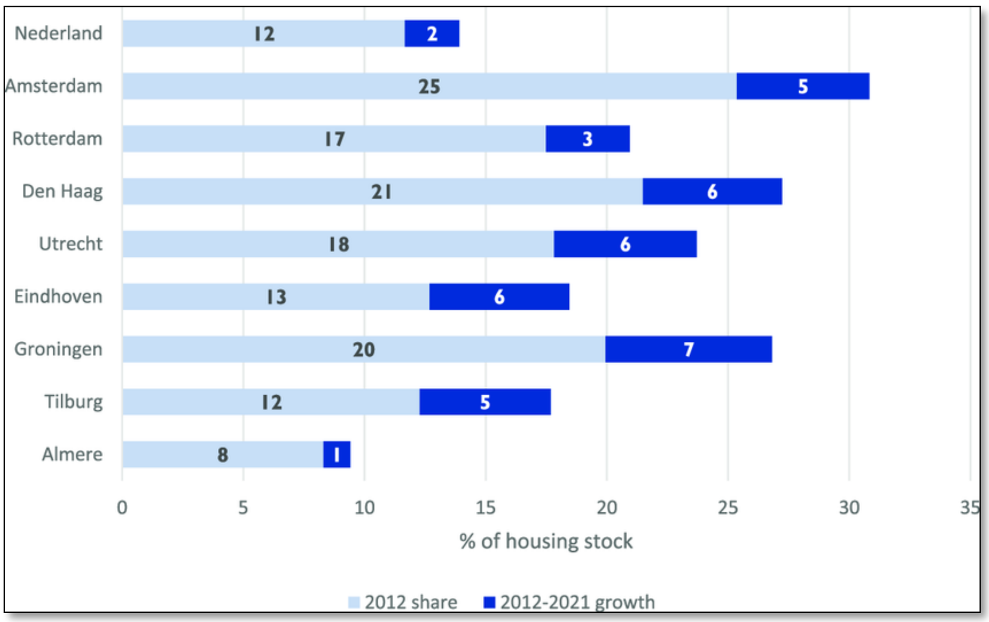

Figure 6. Private-rental housing as share of the total stock in 2012 and subsequent percentage-point growth (2012-2021). Data for the Netherlands and eight largest cities. Source: CBS Statline.

As of 2024, the average rent per square meter in Amsterdam stands at approximately €25.75 (Statista, 2023a). However, this figure varies considerably depending on the location within the city, with central areas typically demanding higher prices.

The average cost for an overnight stay in Amsterdam was higher in 2023 compared to previous years (Figure 7). Over the period considered, the average rate of accommodations in the city peaked at 317€ in April 2023, roughly a 43 percent increase from the same month of the previous year (Statista, 2023b).

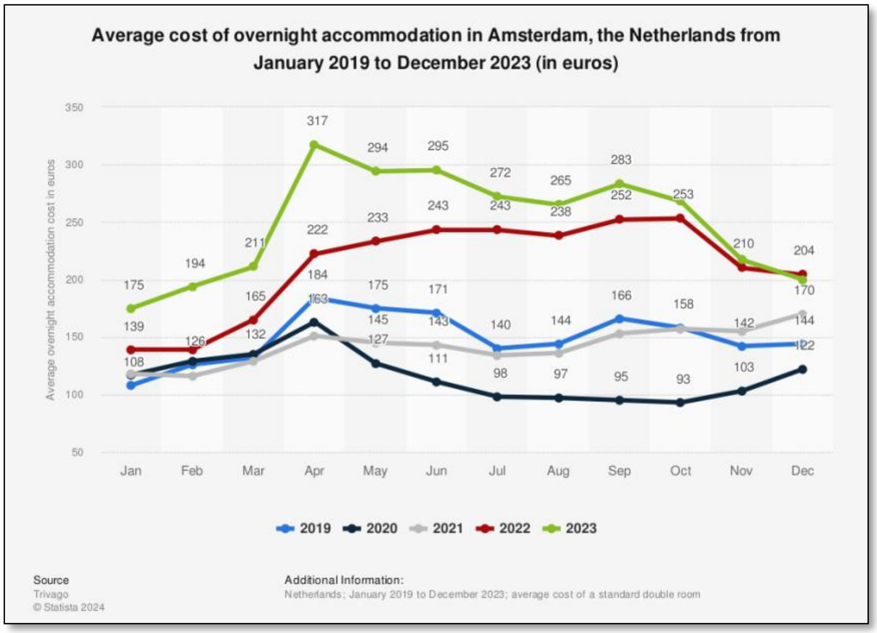

Figure 7. Average cost of overnight accommodation in Amsterdam 2019-2023, by month.

Moreover, when analysing the city's urban planning, certain neighbourhoods stand out as particularly popular with tourists, and are where most short-term rentals are located. These include Centrum-West, which encompasses famous areas such as the Jordaan, the Canal Ring, and the Red-Light District; Centrum-Oost, known for its proximity to attractions like the Artis Zoo and the Hermitage Museum; and De Pijp-Rivierenbuurt, a vibrant area famous for the Albert Cuyp Market. Other key areas include Oud-West, near Vondelpark and the Museum Quarter; Zuid, which includes the Museumplein, home to major museums like the Rijksmuseum and the Van Gogh Museum; and Westerpark, a more residential area known for its large park and cultural events. These neighbourhoods are central to Amsterdam's appeal, attracting both tourists and locals alike (Viator, 2023).

Based on the data extracted from AirDNA, it was straightforward to localize the different neighbourhoods found in the dataset, since the geographical coordinates were provided. A visual representation is here reported to illustrate them, divided into 23 areas, each color-coded and labelled by name (Figure 8). The Amsterdam's neighbourhoods are divided as follows:

- Noord is represented with the red colour and includes Noord West, Noord Oost.

- Nieuw-West is represented with the blue colour and includes Osdorp, Slotervaart, Geuzenveld-Slotermeer-Sloterdijken, De Aker, Sloten en Nieuw Sloten.
- West is represented with the green colour and includes Westerpark, Bos en Lommer, Oud West / De Baarsjes.
- Centrum is represented with the yellow colour and includes Centrum West, Centrum Oost.
- Oost is represented with the orange colour and includes Oud Oost, Indische Buurt / Oostelijk Havengebied, IJburg / Eiland Zeeburg, Watergraafsmeer.
- Zuid is represented with the purple colour and includes Oud Zuid, De Pijp / Rivierenbuurt, Buitenveldert / Zuidas.
- Zuidoost is represented with the pink colour and includes Bijlmer Centrum, Gaasperdam / Driemond.

The division helps in geolocating the areas and adds a layer to the analysis, enabling the evaluation of whether the regulation has affected areas differently.

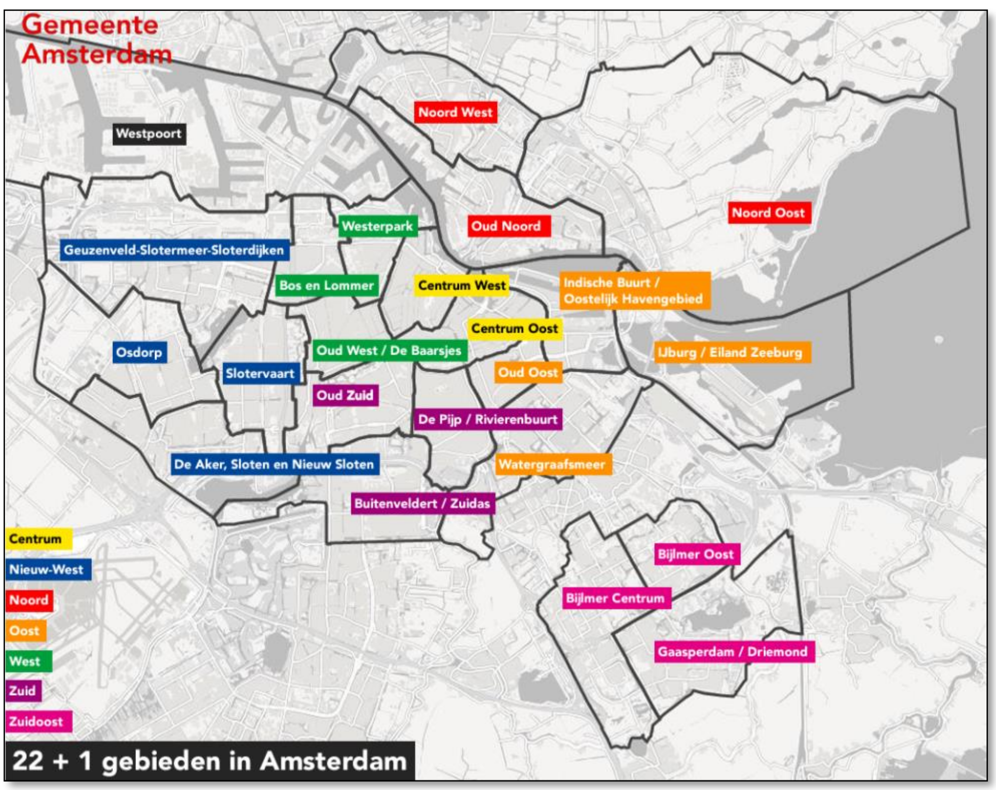

Figure 8. Division of neighbourhood of Amsterdam (Amsterdam, 2018).

b. Amsterdam's regulation framework over time

Amsterdam's unique urban landscape, with its small historical houses and limited space for large developments due to the canals, posed particular challenges when Airbnb began operations in 2008. Initially unregulated, the situation changed in 2013 after a court ruling deemed short-term rentals illegal without proper authorization, prompting the city to introduce a regulatory framework. In 2014, the government enforced limits on un-hosted rentals, restricting them to 60 days per year and up to four guests per rental, while creating a new category for private rentals. Amsterdam adopted a collaborative approach with Airbnb, formalized through a Memorandum of Understanding (MOU), which has been renegotiated annually to address emerging challenges. Notably, Amsterdam was the first European city to sign such an agreement with Airbnb, setting a precedent for other cities to follow.

In 2015, Airbnb began collecting a 5% tourist tax on behalf of the city. However, when platform facilitators refused to share data, Amsterdam introduced a mandatory registration system that linked hosts to their national ID numbers. A 2016 MOU introduced tools to combat illegal hotels and capped short-term rental activity at 60 days per property without a business license. Airbnb also launched a neighbor-reporting tool to address concerns such as neighborhood changes and rising housing prices.

By 2017, an estimated 6,000 Airbnb listings in Amsterdam were illegal (i.e., unregistered), leading to stricter enforcement measures. New tools were introduced to block illegal hosts, along with a 24/7 hotline for reporting issues. In 2018, the tourist tax for peer-to-peer accommodation increased to 6%, and bed and breakfast licenses were limited to 5% of each neighborhood and 25% per building. In 2019, un-hosted rentals were further limited to 30 days per year, and the tourist tax was raised to 7%. Additionally, hosts were required to notify the city each time they rented out their home.

In 2020, Amsterdam raised the tourist tax to 10% and attempted to ban short-term rentals in three districts, a move upheld by the courts. A licensing system was introduced for other districts, and the city temporarily suspended limited permits for bed and breakfasts due to the COVID-19 pandemic.

Currently, managing private vacation rentals, bed & breakfasts, and short stays in Amsterdam requires hosts to register their listings through the City of Amsterdam's website. A permit is mandatory for vacation rentals, while bed & breakfast owners must apply for both a registration number and a permit. The permit is temporary, renewable annually, and valid until April 1 of the following calendar year, regardless of the application date. Under Dutch regulations, the 30-night limit remains in effect unless a specific permit, such as a short-term stay license, is obtained. The City of Amsterdam can request that Airbnb block the calendar for listings that have reached the annual limit. Tourist and income taxes vary depending on the type of rental and length of stay (Airbnb Help Centre, 2024). If you rent or exchange your home in Amsterdam without a registration number, or fail to report the number of nights for a holiday rental in advance, you may be fined €8,700 for each violation, with fines reaching up to €21,750 (Steff, 2024).

Amsterdam's continuous adaptation and collaborative strategies offer insights into effectively managing short-term rentals, balancing economic benefits while minimizing negative impacts on local communities. In alignment with the city's proactive and dynamic regulatory environment, Airbnb has adopted the local government rules, emphasizing their commitment by stating, "We want to help ensure that home sharing grows responsibly and sustainably, and makes Amsterdam's communities stronger." (Airbnb Help Centre, 2024). This makes Amsterdam an interesting case for studying the broader implications of short-term rental regulations in urban areas.

c. The choice of the regulation

After reviewing the situation in Amsterdam, a specific regulation was chosen for this analysis: the 30-day annual limit on short-term rentals of entire homes. This policy stands out as one of the most stringent regulations in Europe regarding short-term rentals and was selected for its potential to have a significant impact on both the housing and tourism sectors in the city. The regulation, implemented on January 1, 2019, applies exclusively to entire homes, while Bed & Breakfasts, private rooms, shared accommodations, and hotels are not subject to this restriction. This distinction makes the regulation particularly useful for analysis, as it allows for a clear comparison between listings affected by the rule (treated group) and those that remain unaffected (control group).

This regulation provides an excellent opportunity to conduct a before-and-after analysis, given the availability of data both pre and post implementation. The data can be segmented based on property type to distinguish between those subject to the regulation and those that are not, in order to obtain a more comprehensive evaluation of the regulation's impact by comparing changes in key metrics, such as occupancy rates, revenues, and the number of active listings, across these different property types.

The rationale behind this policy is multi-faceted and serves both housing market and tourism management objectives. First, the city aims to reduce the number of properties being taken off the market solely for short-term rental purposes. Amsterdam, like many major cities, faces housing shortages, especially for long-term residents like students, families, and workers. The city government hopes that by limiting the rental period for entire homes, more properties will become available for long-term residents. This policy targets individuals or companies who purchase properties exclusively to operate short-term rentals, thus exacerbating the housing crisis by reducing the supply of homes for permanent residents. Secondly, the regulation is also a tool to manage overtourism, a growing problem in Amsterdam. The city is a highly popular tourist destination, which has led to overcrowded neighborhoods, particularly in central areas, where many short-term rental properties are concentrated. By reducing the number of available short-term rentals, the city aims to balance the needs of local communities with the pressures of tourism, helping to preserve the character of residential neighborhoods and prevent them from being overrun by tourists.

Additionally, the regulation reflects an effort to restore the original purpose of platforms like Airbnb — to provide a temporary rental solution for homeowners, rather than allowing these platforms to be dominated by commercial operators looking to profit from short-term rental markets. The city hopes to curb the rise of professional short-term rental businesses that have distorted the housing market, making it difficult for local residents to find affordable, long-term accommodation.

Finally, from an enforcement perspective, the regulation imposes hefty fines on hosts who fail to comply, with penalties reaching up to €21,750. This strict enforcement strategy indicates that Amsterdam is serious about ensuring compliance, making this a highly relevant regulation to analyze in terms of its overall market impact and effectiveness in meeting the policy's goals.

The 30-day limit is thus a pivotal regulation with considerable implications for both the housing market and tourism management in Amsterdam. This analysis will employ a before-and-after approach to examine the effects of this policy, aiming to quantify its impact on different metrics in the hospitality industry, while considering its broader social and economic consequences.

d. The Research Questions

The purpose of this dissertation is to investigate the potential effects of the 30-day annual rental limit for entire apartments in Amsterdam on the Airbnb market. To assess this, the analysis will employ a combination of descriptive statistics and a regression model, utilizing the Difference-in-Difference (DiD) approach to compare pre- and post-regulation trends. By contrasting treated listings (entire apartments subject to the regulation) with control listings (private/shared/hotel rooms not subject to regulation), the study aims to uncover both the broader and more specific impacts of the regulation. A detailed explanation of the DiD methodology will be provided in the following chapter.

The following research questions and hypotheses have been formulated to guide the analysis. These questions will serve as the foundation for understanding how the regulation has influenced various market metrics, such as the supply of listings, occupancy rates, demand for Airbnb properties and prices.

Research Question 1

"Has the introduction of the 30-day rental limit affected the supply of Airbnb properties?"

This question seeks to explore whether the 30-day annual rental limit has influenced the Airbnb market in Amsterdam, specifically focusing on the supply of listings. It is hypothesized that restricting the number of days an entire apartment can be rented may lead to a reduction in the overall number of active Airbnb listings or a decrease in the total available days for those listings. This change in supply could reflect hosts withdrawing their properties from the platform or reducing their availability in response to the regulation.

Hypothesis 1: The 30-day rental limit is expected to result in fewer Airbnb listings, particularly entire apartments. Additionally, it is hypothesized that the total number of available days per listing may decrease over time, as the regulation limits hosts' ability to rent their properties.

To test this hypothesis, the key metric to analyze is the number of Available Nights, which is reported monthly.

Research Question 2

"Has the regulation imposing 30-day rental limit influenced the demand of Airbnb properties?"

This question seeks to determine whether and to what extent the 30-day rental restriction has affected the demand for Airbnb listings in Amsterdam and it examine if the size of the impact on the different types of listings. The analysis will focus on two key dependent variables: the number of people staying in Airbnb listings and the occupancy rate.

Hypothesis 2: It is hypothesized that the 30-day limit has led to a reduction in demand, particularly in terms of the number of people staying in entire apartments. Listings affected by the regulation may see fewer guests compared to unaffected listings, as the reduced availability makes it less attractive for potential renters.

To calculate the number of people staying in Airbnb properties on a monthly basis, we will use the following formula: Number of People = Max Capacity (Guests) × Number of Reservations.

This allows us to estimate the total number of individuals staying in a given Airbnb listing, assuming that each reservation fills the listing to its maximum capacity.

The occupancy rate, on the other hand, will be calculated as the ratio of Reservation Days to the sum of Reservation Days and Available Days. It is expected to decrease slightly, but not significantly, due to its strict relation with external factors like seasonality, local events, and market demand, which may still sustain bookings.

Research Question 3

"Has the regulation imposing 30-day rental limit impacted the Airbnb revenues per listing?"

This research question examines the potential financial effects of the 30-day rental limit on hosts' revenues. Specifically, it aims to explore whether the restriction on the number of rental days has pressured hosts to adjust their pricing strategies to maintain profitability. One key pricing metric used in the analysis is the Average Daily Rate (ADR), which measures the average revenue earned per night a listing is rented.

Hypothesis 3: It is hypothesized that the regulation may lead to an increase in the ADR for listings affected by the 30-day rule, as hosts attempt to offset the reduction in the total number of rental days by charging higher rates. This adjustment may be particularly evident for entire apartments, compared to other types of listings not affected.

To explore this hypothesis, the key data to analyze are the revenue per night (ADR) and monthly revenues, segmented by listing type (entire apartment vs. private/shared room), before and after the implementation of the regulation.

These research questions are designed to provide a detailed understanding of how the 30-day rental limit might have impacted Airbnb's supply, demand and prices in Amsterdam. Through descriptive and statistical analysis, the study aims to shed light on the broader effects of this regulatory change.

4. Research Methodology

This section outlines the research methodology employed in this study, focusing on three main components: the overall Research Process and analysis, data collection, and the tools used. First, the process of analysis will be explained, including the steps taken to examine the data and the process to test the research hypotheses related to the impact of Airbnb regulations. Following this, the data collection process will be discussed, detailing the sources of the data, the criteria for selection, and what metrics have been added to build a more comprehensive dataset. Lastly, the tools utilized for data analysis will be outlined, covering the software and statistical methods applied throughout the research.

a. The Research Process

The research process begins with the formulation of hypotheses derived from the research questions. The primary aim of this analysis is to answer these questions and empirically test the hypotheses. This process is structured in two main phases: an initial Exploratory Analysis using descriptive statistics, followed by a more formal econometric analysis that employs the Difference-in-Difference (DiD) method as part of a broader Regression framework.

The first phase involves Exploratory Data Analysis (EDA), which serves as a foundation for understanding the dataset and identifying broader trends, patterns, and correlations. This descriptive analysis helps highlight key variables and relationships within the data, offering valuable insights that inform the subsequent hypothesis testing. While this phase does not seek to establish causal relationships, it sets the stage for more rigorous statistical methods by providing a comprehensive overview of the data.

To test the formulated hypotheses, the study applies a Difference-in-Difference (DiD) approach within a regression analysis framework. The DiD method is a widely used econometric technique for evaluating policy interventions, particularly suited for analyzing causal impacts over time. This approach compares the differences in outcomes between a treatment group (affected by the regulation) and a control group (unaffected), both before and after the policy's implementation. By using a regression model, the DiD method controls for time-invariant characteristics of both groups, as well as broader trends, thus isolating the effect of the regulation on the variables of interest.

In this study, the DiD method is integrated into a regression analysis to further explore and quantify the relationships between the variables. This allows for a more precise estimation of the impact of Airbnb regulations on key metrics, such as the number of listings and market dynamics. By combining descriptive statistics with regression techniques, this research provides a robust understanding of how regulatory changes have influenced the Airbnb market in Amsterdam.

b. Data Collection

The primary data sources for this analysis were obtained from the AIRDNA website and they include all data from Airbnb. Additionally, official websites of the Amsterdam local government and Inside Airbnb website were consulted, along with open access data from municipal databases. Publications from the tourism and real estate industries were also reviewed to gain a comprehensive understanding of the global and local context.

The main dataset represented all Airbnb listings active in Amsterdam from 2017 to mid-2024 on a monthly basis. The analysis encompassed over 800,000 rows of data, representing nearly 60,000 distinct listings over the years.

Every row represents a property for a given month and has a set of variables reported below.

- Property Information: Property ID, Property Type, Listing Type, Number of Bedrooms, Number of Bathrooms, Max Guests, Price Tier, Creation Date, Minimum Stay.
- Geographical Information: City, Neighborhood, Metropolitan Statistical Area, Latitude, Longitude.
- Performance Metrics: Revenue (USD), Number of Reservations, Reservation Days, Available Days, Overall Rating.
- Host Information: Airbnb Host ID, Host Type, Airbnb Super Host.

- Time Information: Reporting Month, Year.
- Other Information: Cancellation Policy level.

In the table below each metric is described in detail.

External Name	Data type	Description
Property ID	VARCHAR (16777216)	Airbnb's unique identifier for the property
Reporting Month	TIMESTAMP_NTZ(9)	Monthly period that the data is run for in this monthly report
Revenue (USD)	NUMBER (38,0)	Monthly Revenue for the listing in US Dollars ($)
Number of Reservations	NUMBER (38,0)	Number of reservations in the current Month for the listing
Reservation Days	NUMBER (38,0)	Total number of days reserved in the current month for the listing
Available Days	NUMBER (38,0)	Total number of days that the listing remained available and un-booked in the current month
Airbnb HOST ID	VARCHAR (16777216)	Unique Airbnb host ID
Listing Type	VARCHAR (16777216)	Three vacation rental listing types: Entire Home, Private Room, and Shared Room
Host Type	VARCHAR (16777216)	Property's host type based on number of units they have. Classified into 1 Unit, 2-5 Units, 6-20 Units, or 21 Units
Neighborhood	VARCHAR (16777216)	Neighborhood where the vacation rental property is located, where available
Latitude	NUMBER (20,18)	Latitude of the vacation rental property (see Exact Location for Accuracy)
Longitude	NUMBER (20,18)	Longitude of the vacation rental property (see Exact Location for Accuracy)
Price Tier	VARCHAR (16777216)	Average daily rate price in segments listings within a market into different price points: budget, economy, midscale, upscale, luxury

Bedrooms	NUMBER (38,0)	Number of bedrooms in a vacation rental listing
Bathrooms	NUMBER (38,0)	Number of bathrooms in a vacation rental listing
Max Guests	NUMBER (38,0)	Number of Guests that the listing can accommodate
Cancellation Policy	VARCHAR (16777216)	Cancellation policy for the vacation rental listing
Minimum Stay	NUMBER (38,0)	The default minimum night stay required by host
Created Date	TIMESTAMP_NTZ(9)	The date the vacation rental listing was created
Airbnb Superhost	BOOLEAN	True or False depending if the host is a Superhost on Airbnb
Overall Rating	NUMBER (38,0)	Average guest rating of the property out of 100

In addition to the metrics already present in the database, other variables were calculated using the available data, adding new columns to the dataset for further analysis. The main calculated variables are listed below.

- Occupancy Rate as number of Reservations Days over the total availability in the given month, for every listing – to study availability patterns.
- Average Daily Rate (ADR) as total revenue over the number of booked nights. The monthly ADR is an important metric in the hospitality industry and it will provide insights on the overall pricing strategy. It indicates the average revenue per booked night in USD dollars.
- Revenue per Available Room (Rev PAR) as the multiplication of the ADR and the occupancy rate. It is more precise since it takes into consideration also the available days in the count of the revenues.
- Number of People as the number of guests staying in the property for the given month. The metric was calculated based on the assumption that the apartment was fully booked when reserved. The number of people is given by the product of the Maximum Guest capacity of each listing and the Number of Reservations made in the given month.

After gaining a thorough understanding of the columns the database was cleaned for the research scope. The year 2024 was excluded from all graphs and analyses due to incomplete data, making it insignificant for a full-year comparison. Additionally, blank values were omitted, and each metric was carefully checked to ensure relevance and significance.

c. Tools used

To effectively analyze the dataset, two primary tools were employed: Excel and Stata, each chosen for their specific strengths in managing different aspects of the research process. These tools allowed for both efficient handling of preliminary data and more complex, detailed statistical analysis, which together supported a comprehensive examination of the effects of Airbnb regulations on the Amsterdam market.

Excel played a crucial role in the early stages of the research. Known for its versatility and accessibility, Excel is a widely used tool for data management and initial data analysis. In this study, Excel was used for tasks such as data cleaning, ensuring that the dataset was free from inconsistencies or missing values that could affect subsequent analysis. This step is vital in any empirical research as clean, well-structured data is the foundation for accurate and reliable results. Excel's ability to sort, filter, and manipulate data allowed for the efficient identification and correction of potential issues, making it an ideal platform for organizing the dataset before more advanced methods were applied.
Another key feature of Excel used in this phase was its ability to generate simple visualizations such as charts and graphs, which helped in gaining initial insights into the dataset. These visualizations provided a preliminary understanding of trends and distributions, offering a clear starting point for more in-depth analysis later in the process. Furthermore, pivot tables were extensively used to summarize and aggregate data across different variables, facilitating the exploration of patterns and relationships within the dataset.

Once the data was organized and preliminary insights were obtained, the analysis moved into the more advanced phase, which required the use of Stata. As a powerful statistical software package designed for high-level data analysis, Stata was essential for conducting econometric techniques that Excel could not handle. One of the most critical analyses performed in this study was the Difference-in-Difference (DiD) analysis, a method commonly used to assess the impact of policy changes by comparing the outcomes of treated and untreated groups over time. Stata’s robust capabilities made it possible to implement this method with precision, allowing the study to control for time-invariant factors and general trends that might have influenced the results.

In addition to the DiD method, Stata was used to run various regression models that explored the relationships between variables in more detail. These models helped to test the research hypotheses and quantify the effects of Airbnb regulations on specific metrics, such as the number of listings. Stata's support for advanced statistical techniques, including heteroskedasticity-consistent standard errors, fixed effects models, and interaction terms, ensured that the analysis accounted for potential biases and confounding variables, increasing the accuracy and robustness of the findings.

Beyond its analytical capabilities, Stata also offered sophisticated data management features that facilitated the handling of large, complex datasets. Its ability to merge, reshape, and manipulate data was particularly valuable in ensuring that all relevant variables were integrated into the analysis without data loss or errors. Furthermore, Stata's graphical tools allowed for the creation of high-quality visual outputs, such as regression diagnostics and trend plots, which were crucial for interpreting and presenting the results in a clear and concise manner.

The combined use of these tools provided a structured and comprehensive approach to the research and it supported the study’s aim of evaluating the impact of Airbnb regulations on Amsterdam’s housing market.

5. Exploratory Data Analysis

The Exploratory Data Analysis (EDA) was conducted using descriptive statistics, a branch of statistics focused on the collection, synthesis, and interpretation of data. This step is crucial in any data-driven research as it lays the foundation for understanding the characteristics and underlying patterns within the dataset. Descriptive analysis involves calculating basic statistics to gain insights into the distribution, central tendencies, and variability of the data, which helps formulate hypotheses for deeper analyses.

The purpose of this descriptive analysis is to explore the relationships between key economic variables within the context of Airbnb's presence in Amsterdam, with particular focus on the impact of regulations introduced in 2019. The analysis is based on panel data, covering monthly observations from 2017 to 2023. The primary variables of interest are grouped into three categories: (i) supply-side variables, (ii) demand-side variables, and (iii) price-related variables. By structuring the analysis around these categories, we aim to examine how the new regulations influenced Airbnb's market presence, specifically regarding supply (number of rentable nights and number of listings), demand (number of people staying and occupancy rate), and prices (average daily revenue). Additionally, the analysis differentiates between treated and control groups to assess the heterogeneous effects of the policy changes.

It is also important to note the significant impact of the COVID-19 pandemic in 2020 and 2021, which drastically affected both the Airbnb sector and everyday life. While certain trends can still be observed and analyzed, disentangling the effects of the pandemic from those of the regulations remains a challenge. In the following chapter, a regression analysis will be carried out to further investigate these phenomena using statistical methods.

a. First Descriptive Analysis: Impact on the supply of Airbnb's offerings

The objective of this descriptive analysis is to assess the impact of the 2019 regulations on Airbnb's supply of properties, with a particular focus on how the availability of listings and the number of available nights on the platform have changed in response to these regulatory measures.

i. Number of Distinct Listings and Hosts

To investigate this trend the number of distinct listings and the number of distinct hosts over time were calculated. These metrics help provide a more detailed understanding of how the supply side of the Airbnb market has evolved and they give an idea of the size, coverage and ownership of the service the city is offering.

The graph below (Figure 9) shows a clear decline in the number of Airbnb listings. In 2017, there were around 33,960 listings, but the numbers dropped dramatically over the years (-67% until 2021). This decline is likely related to the impact of the COVID-19 pandemic in the last 2 years, but at the same time it can be related also to stricter regulations implemented continuously in the last years. Even by 2023, the number of listings slightly increased, reaching 11,364 — just +2% in two years – but the general trend is that Airbnb presence is clearly decreasing.

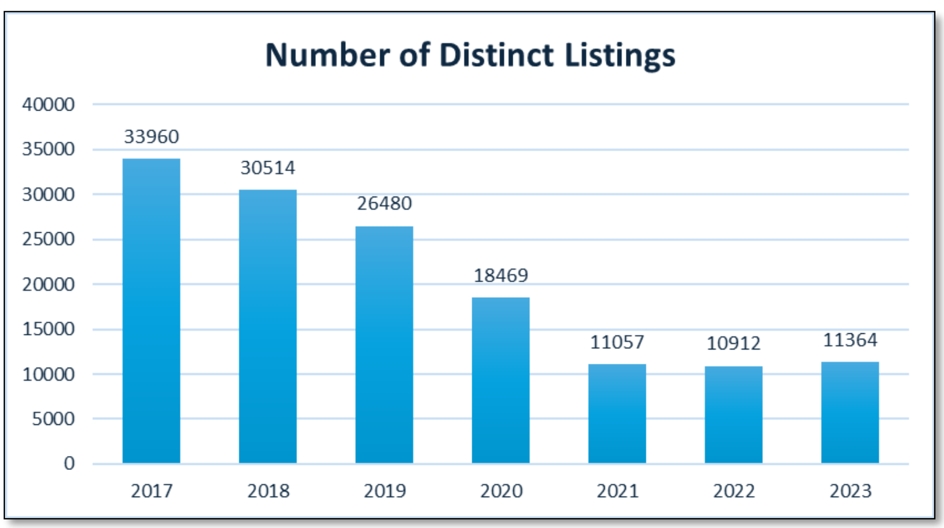

Figure 9. Number of distinct Airbnb Listings over the years 2017-2023.

As expected, the number of hosts follows a similar trend to the decline in listings (Figure 10). In 2017, there were 25,491 hosts, but by 2023, that number had dropped to 9,380 (-66%). This decline likely reflects a combination of factors, including hosts leaving the platform due to stricter regulations and reduced profitability as new rules were implemented.

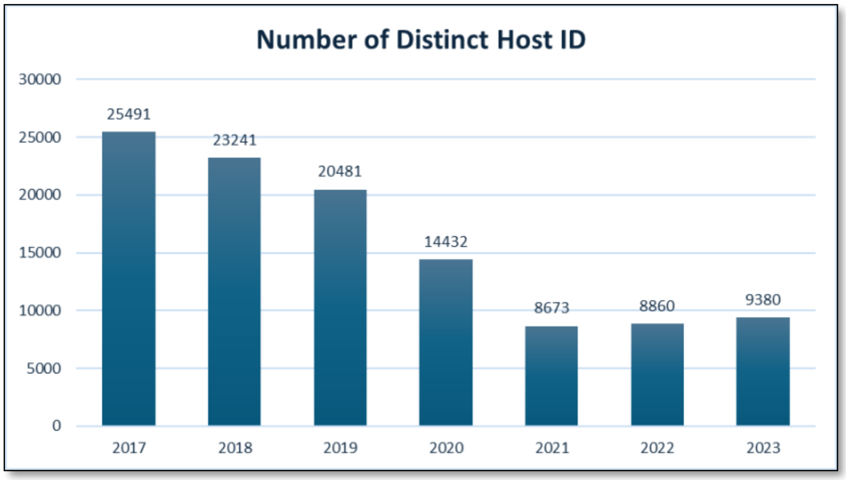

Figure 10. Number of distinct Host over the years 2017-2023.

In the chart below (Figure 11) the difference in the decrease is further distinguished by listing type. The treated group experienced a sharper decrease, with listings dropping by 71%, compared to a 62% decrease in the control group. This significant decline aligns with the previously discussed reduction in hosts and listings, highlighting the substantial impact of regulations on Airbnb's market presence over time, particularly for entire home listings.

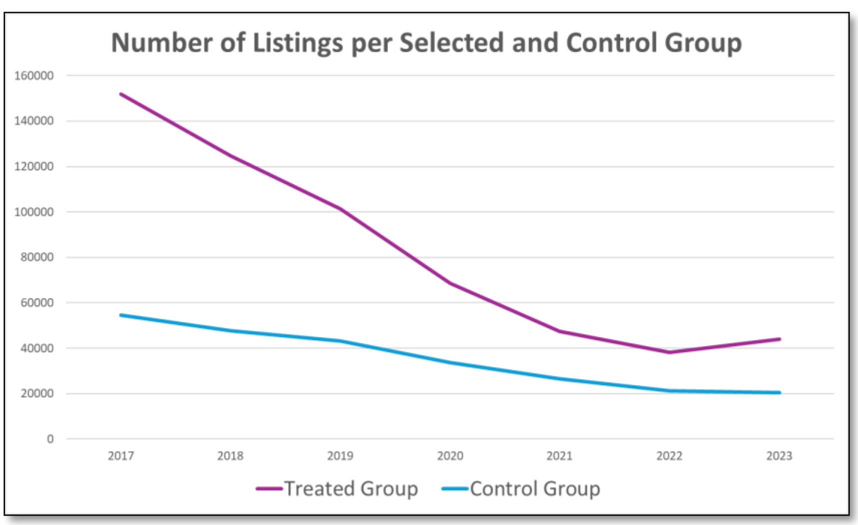

Figure 11: Number of listings over time divided per treated and control group.

ii. Number of monthly Available Days

In this analysis, another important supply-side variable is examined: the available days, defined as the number of nights a listing is available for booking. The first graph (Figure 12) shows the total available days per month for the treated and control groups from 2017 to 2023. Overall, the treated group consistently has significantly more available days than the control group. However, after 2019, a slightly more pronounced decline is observed for the treated group. When comparing 2017 with 2023, the reduction is -77% for the treated group and -73% for the control group. This drop can be attributed to the regulation introduced in 2019 that severely restricted properties in how frequently they could be rented, leading to a steep decline in overall availability.

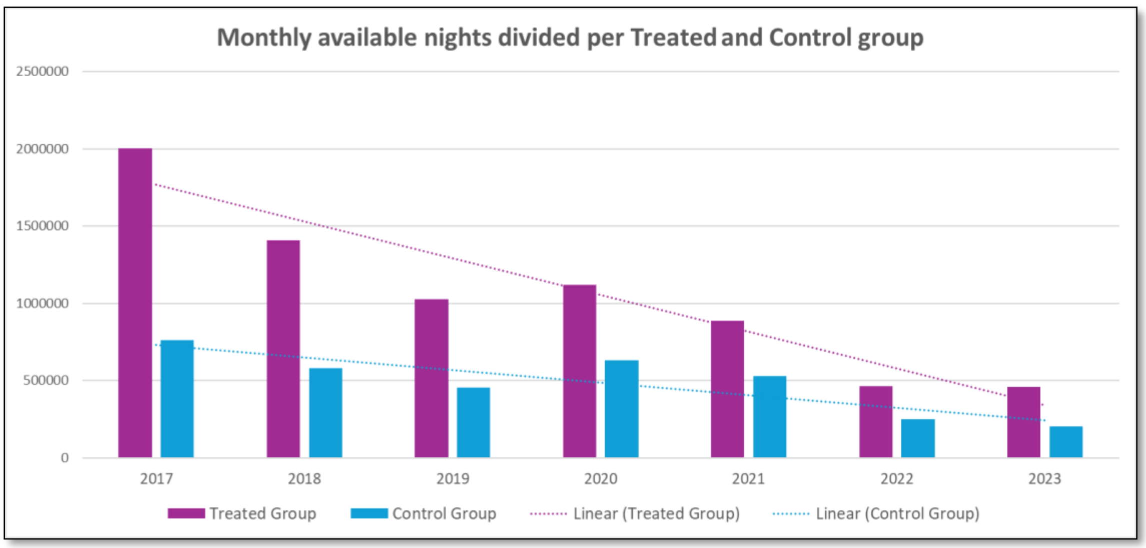

Figure 12. Total available nights over time divided per treated and control groups.

The second chart (Figure 13) further illustrates this trend by reflecting the average available days for both groups. The trend is less evident, possibly because the decrease is more related to the reduction in the number of properties rather than the average number of available days per property. Additionally, the average does not account for factors like seasonality, meaning hosts may simply shift their available days to busier periods of the year. Nevertheless, we observe a slight decrease in the average number of available days over the years, with a -28% reduction for the treated group and -14% for the control group between 2017 and 2023.

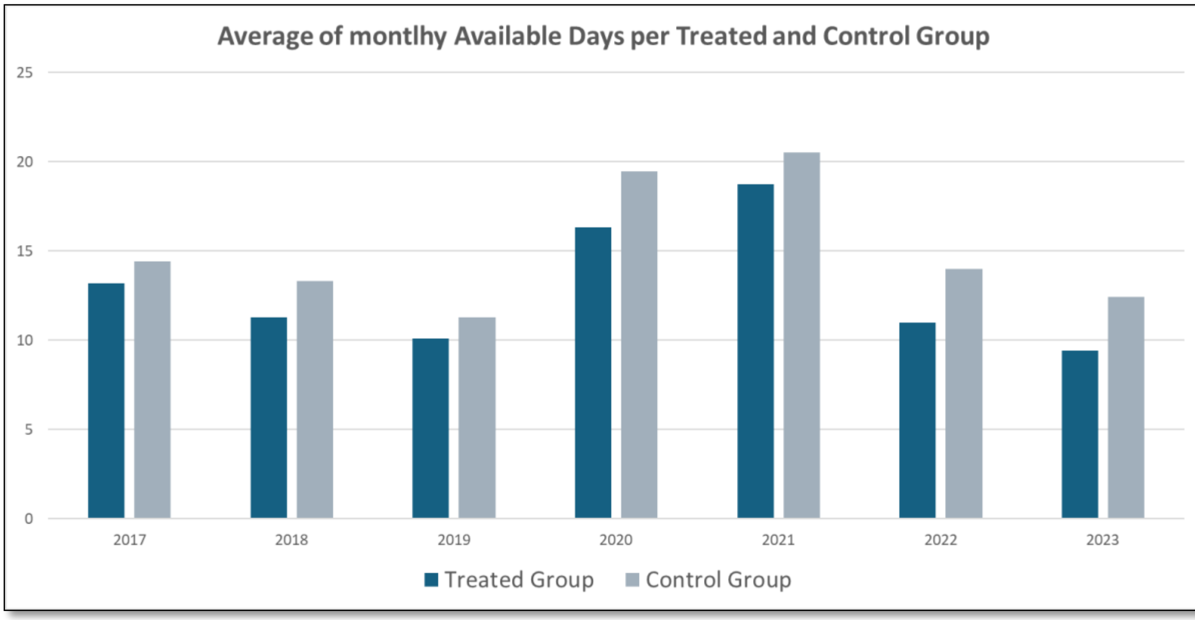

Figure 13. Average of available nights over time divided per treated and control groups.

This descriptive analysis reveals a significant reduction in Airbnb supply, with a sharp decline in the number of listings and hosts, particularly in the treated group. Additionally, the number of available nights has decreased over time, especially for entire apartments, likely due to the regulations introduced in 2019.

b. Second Descriptive Analysis: Impact on Airbnb demand

This section examines how Airbnb demand has evolved in response to the 2019 regulations, taking into account both the treated (entire homes/apartments) and control groups (shared/private rooms, hotel rooms). To understand demand, two primary variables were analyzed: the number of people staying in Airbnb properties and the occupancy rate.

i. Number of People

Using the AirDNA dataset, an estimate of the number of people staying in Airbnb properties was calculated and defined as “Number of People” in the dataset, while here is showed as “Airbnb Guests”. The metric is compared with the overall tourism trends in Amsterdam, measured by the number of visitors to the city over the same period and sourced from the Amsterdam Tourism Statistics website (Amsterdam Tourism Statistics, 2023). The graph below (Figure 14) tracks the number of visitors from 2012 to 2023 and serves as a proxy for the overall demand in the city's accommodation sector, providing context for how external factors, such as regulatory changes or the pandemic, may have impacted both tourist behavior and Airbnb usage.

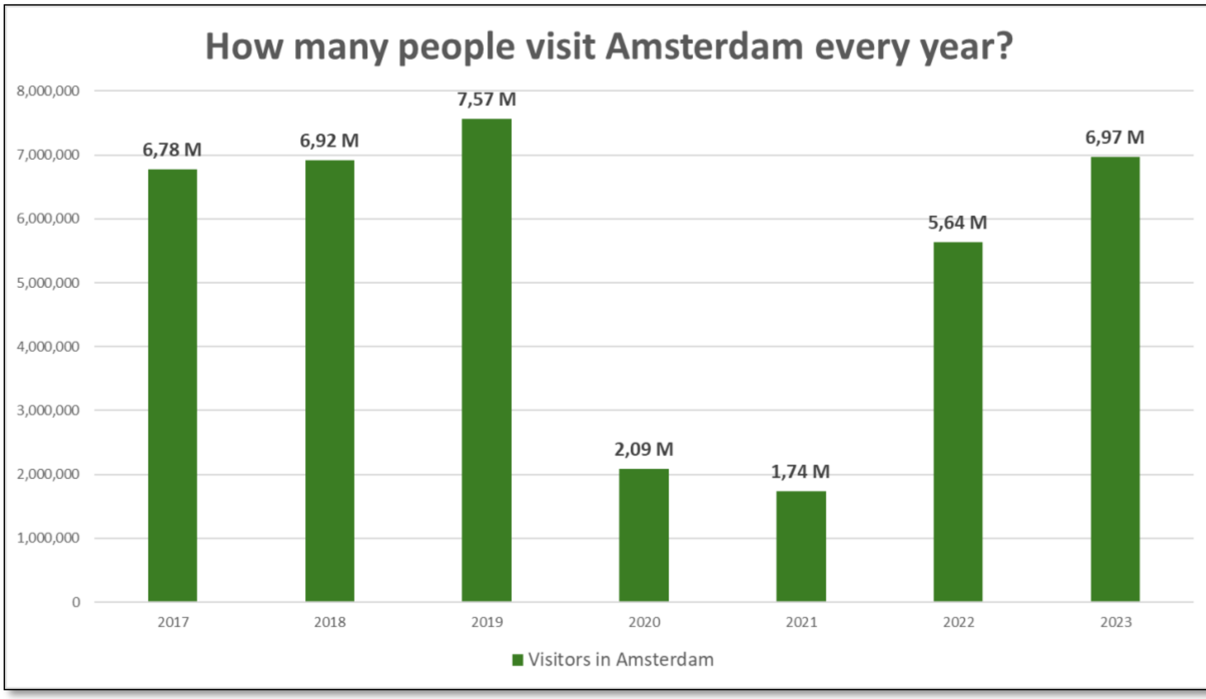

Figure 14. Number of tourists visiting Amsterdam over the years 2012-2023 (in millions).

By comparing this estimated number of Airbnb Guests to the total number of tourists visiting Amsterdam each year, it is possible to determine the percentage of tourists who chose to stay in Airbnb accommodations compared to the total tourists. This relation helps shed light on the role of the sharing economy in Amsterdam's broader tourism landscape over time (Figure 15).

Analyzing the graph, it is noticeable a shift in the usage of Airbnb accommodations over time. Up until 2020, Airbnb accounted for around 20% of the total accommodations, with a slight decreasing trend. However, in 2020, there was a sharp increase to nearly 30%, which can likely be attributed to the COVID-19 pandemic. Given the reduced number of tourists in

2020 (around 2 million compared to 7.5 million in 2019), it is plausible that the few who did travel preferred the privacy of an Airbnb apartment over staying in more crowded environments like hotels or hostels. This made Airbnb a more attractive option during this period of heightened health concerns. In 2021, a similar trend is tracked, with a slight decrease from the 30% peak. However, the most significant decline occurs in 2022 and 2023, where the percentage of tourists opting for Airbnb drops to around 10%. Despite the number of tourists returning to pre-pandemic levels, particularly in 2023, the percentage of Airbnb users does not rebound and instead falls to nearly half of pre-COVID levels.

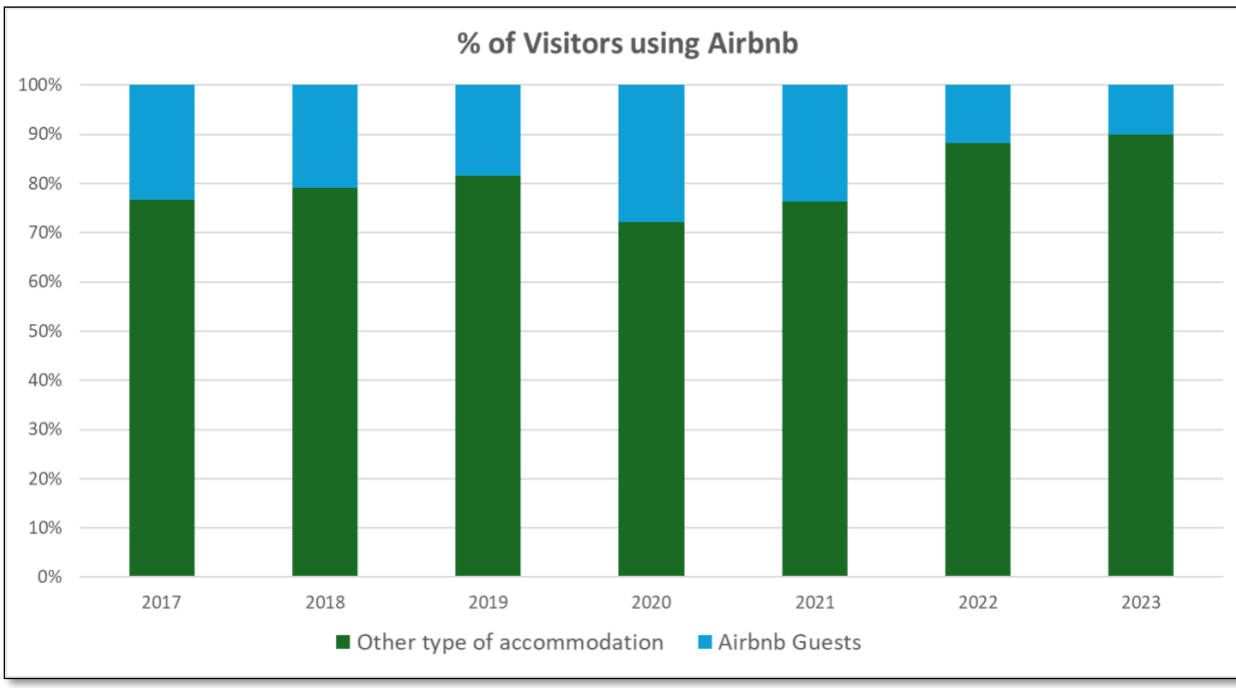

Figure 15. Distribution of Visitors in Amsterdam based on Airbnb Adoption (2017-2023).

When analyzing only the number of guests staying in Airbnb, divided by listing type, a clear difference in trends emerges (Figure 16). The Treated group (entire homes) shows a more pronounced decline in guest numbers compared to the Control group (shared rooms, private rooms, and hotel rooms), even after the COVID-19 years (2020 and 2021). By 2023, the gap between the two groups had significantly narrowed, with both treated and control groups reaching similar guest numbers. Specifically, the average number of Airbnb guests for entire homes decreased by 65%, while the number of guests for shared, private, and hotel rooms decreased by only 32%.

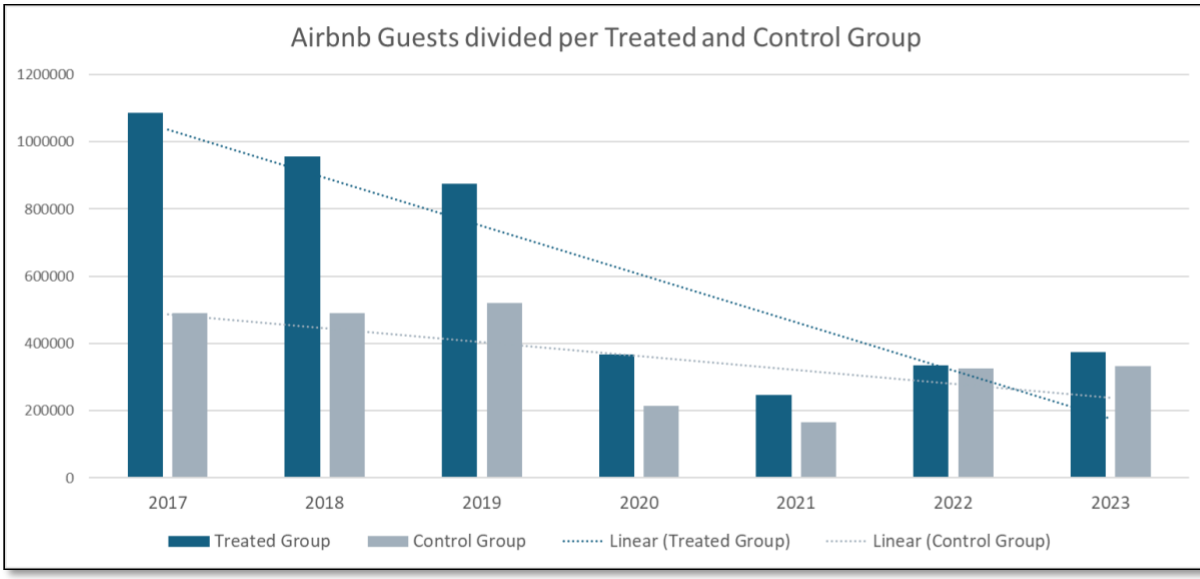

Figure 16. Number of people staying in Airbnb over the years, divided per treated and control groups.

The number of people using Airbnb seems to slightly decrease over time when compared to the overall tourist demand, especially in apartments. The shift in the Airbnb supply and offerings due to the regulatory change is one of the main possible drivers of this change.

ii. Occupancy Rate

Analyzing another variable that can be associated with Airbnb's demand side, we turn our attention to the occupancy rate. Contrary to what might be expected, the occupancy rate did not follow the same consistent decline observed in the number of listings and hosts. Instead, it exhibited fluctuations over the years. As shown in Figure 17., the occupancy rate increased steadily until 2019, reaching a peak of 56.95%. However, there was a sharp decline in 2020 and 2021, likely due to the COVID-19 pandemic, with the rate falling to a low of 26.39%. A strong recovery occurred post-pandemic, with the rate bouncing back to 56.92% in 2023.

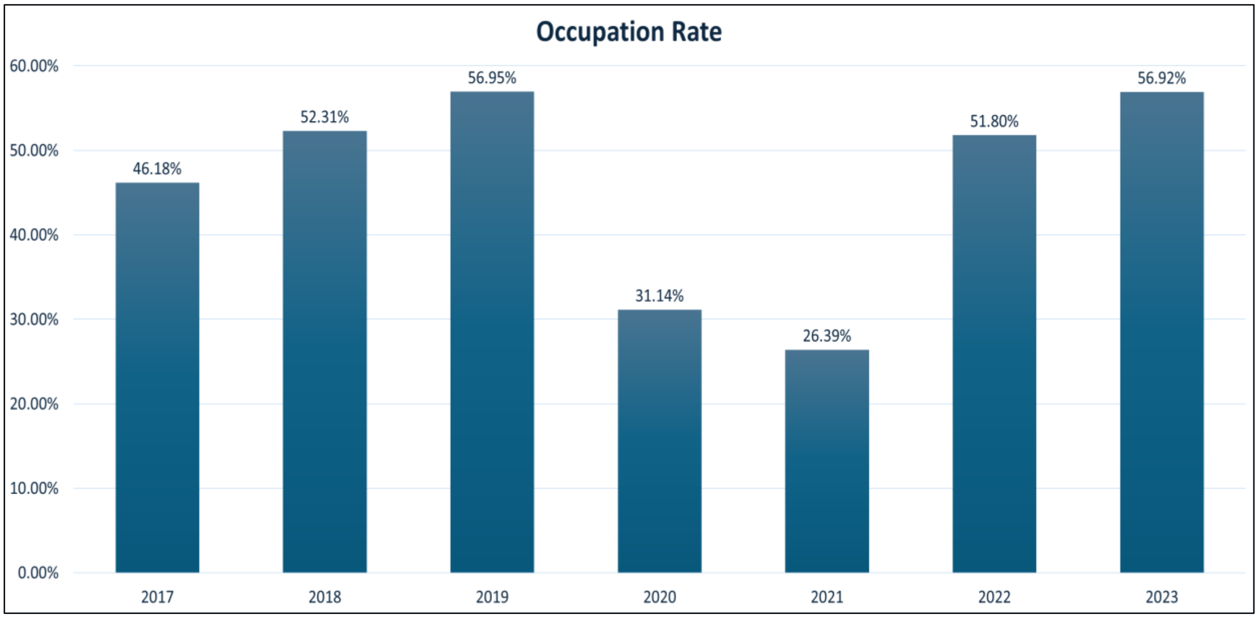

Figure 17. Occupancy rate over the years 2017-2023.

This trend suggests that the regulations did not drastically affect the occupancy rate. This makes sense, as demand for Airbnb accommodations remained active, with customer preferences relatively unchanged. The lower number of people staying in Airbnbs is likely due to the reduced number of listings, which may have been influenced by the new regulations. However, the listings that remained available still maintained a relatively stable occupancy rate, showing resilience in demand.

Additionally, there are few differences between the treated and control groups. Before 2019, entire homes (treated group) showed slightly higher occupancy rates compared to shared or private rooms (control group). Post-regulation, this trend reversed slightly, with private and shared rooms now having marginally higher occupancy rates. Nevertheless, the differences between the two groups remain relatively minor, indicating that the regulations did not significantly alter occupancy patterns. It's also worth noting that the COVID-19 pandemic had a major impact on this metric, further complicating the interpretation of the regulation's effects (Figure 18).

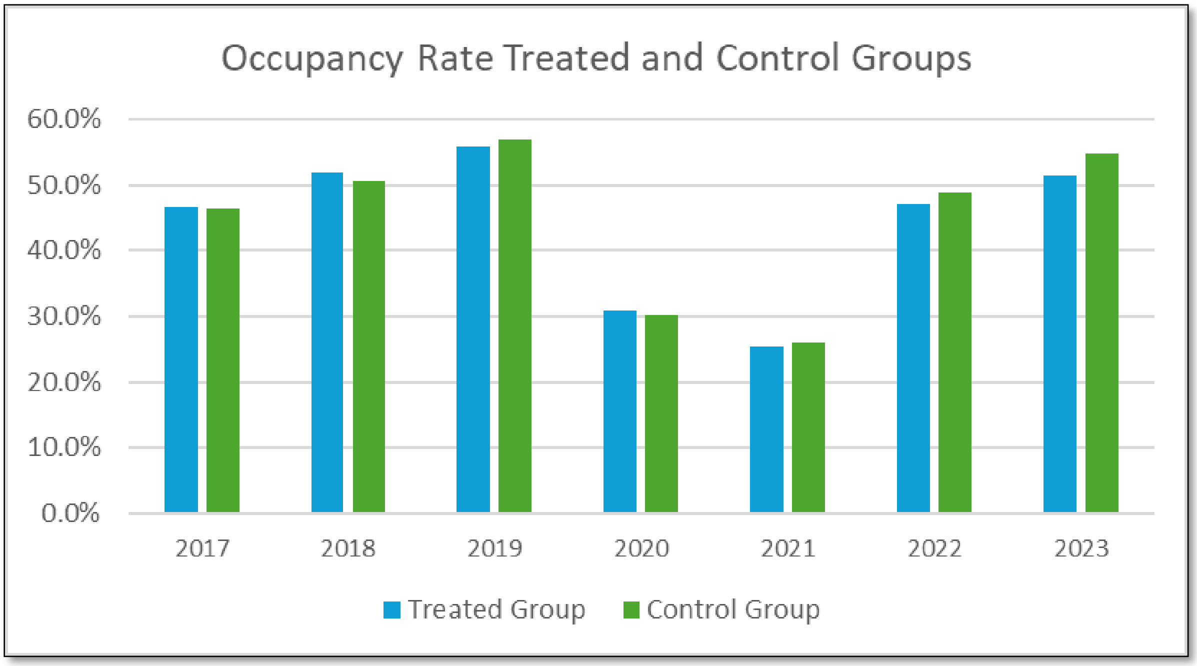

Figure 18. Occupancy rate over time divided per treated and control groups.

This descriptive analysis, that comprehends both the number of people using Airbnb and the occupancy rate, suggests that there must be an additional factor influencing the declining trend in Airbnb usage beyond the pandemic or tourist demand. Regulatory changes and consequently supply might be responsible for this decline in the percentage of visitors using Airbnb.

c. Third Descriptive Analysis: Impact on Prices

In the third descriptive analysis, the focus is on the average revenue per night, known as ADR (Average Daily Revenue) across different Airbnb listing types. The objective is to examine whether the 2019 regulations, which imposed a 30-night-per-year limit on entire apartments, impacted revenue per night. The hypothesis suggests that the regulation likely contributed to an increase in prices for tourists, leading to higher revenues for hosts.
Overall, the average revenue per night increased from $117.9 in 2017 to $217.7 in 2023, reflecting an 84% growth over the period (Figure 19).

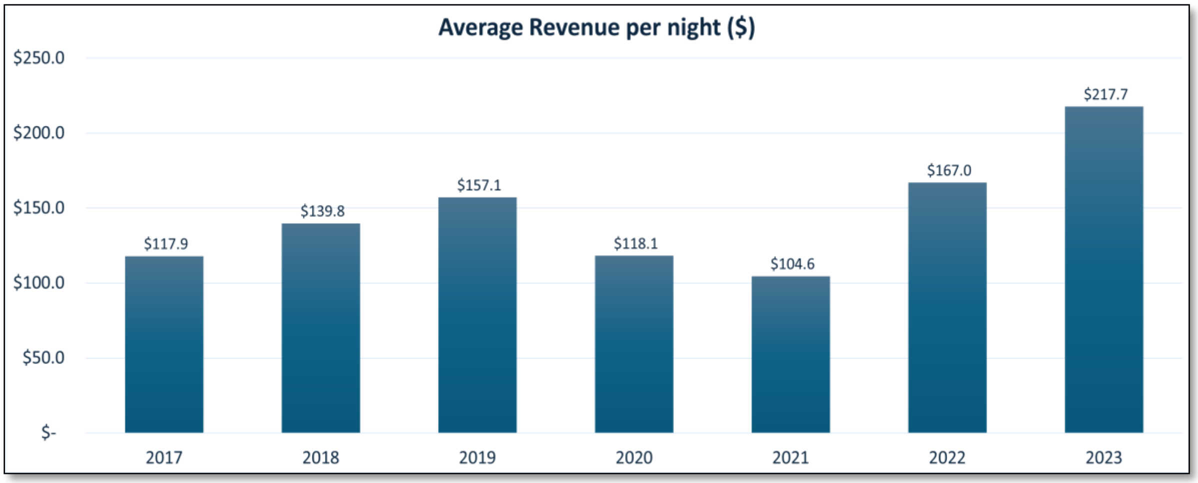

Figure 19. Average Revenue per night in dollars over the years 2017-2023.

However, when the data is broken down by the treated and control groups, a notable difference in trends emerges (Figure 20). The treated group, which includes entire homes, experienced a significant 87% increase in average revenue per night, reaching $242 in 2023. In contrast, the control group, consisting of shared rooms, private rooms, and hotel rooms, saw a more modest rise of 63%, with the average revenue per night reaching only $170 by 2023.

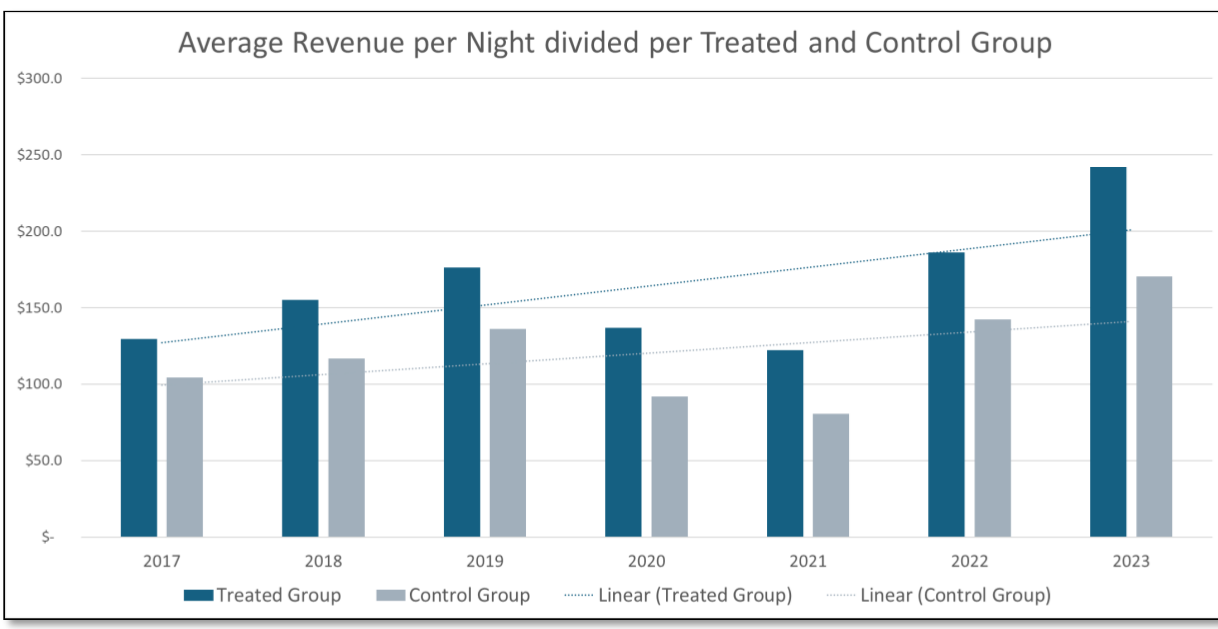

Figure 20. Average revenue per night over time, divided per treated and control groups.

This upward trend in revenue for the treated group could be influenced by several factors. While inflation has generally driven up prices across the board, leading to an increase in nightly rates for all types of listings, the more pronounced rise in the treated group may be directly tied to the regulatory cap on entire apartments. With the supply of available entire homes limited to just 30 nights per year, this restriction likely pushed prices higher due to scarcity, creating upward pressure on average prices per night. Consequently, this dynamic could explain why hosts in the treated group are seeing higher revenues despite operating under stricter limitations. In contrast, the control group, with fewer restrictions on availability, did not experience the same level of price increases, reflecting the more moderate growth in revenue per night.
While this upward trend in revenue is certainly linked to inflation, which has risen significantly in recent years, it is still valuable to study this variable to assess whether the 2019 regulation had an additional impact on prices by creating scarcity in the market.

d. Results of EDA

In conclusion, the descriptive analysis reveals several key trends regarding Airbnb metrics and its evolution in the years 2017-2023. Based on the three-hypothesis made in the third chapter it is possible to conclude that:

- Supply impacts:
    - The number of Airbnb listings decreased by 67%, divided in -71% for the treated group and -62% for the control group.
    - The number of Hosts ID decreased by 66%.
    - The nights available decreased in total by 76%, the monthly average value decreased by 28% for the treated group and by 14% for the control group.
- Demand impacts:

    - The Airbnb adoption (measured with the number of people using the platform) compared to the overall demand of tourists seems to have decreased from ~20% in 2017 to ~10% in 2023.
    - The number of people using Airbnb decreased by 65% for the treated group and by 32% for the control group.
    - For the occupancy rate the trend is less defined in the different groups. It is clear the effect of the COVID-19 pandemic where values reached ~30% while before and after was more than 50%.
- Price impacts: the average revenue per night has increased by 84%, divided in +87% for the treated group and +63% for the control group.

Collectively, these findings show that the 2019 regulations, along with external factors like the COVID-19 pandemic, had a significant impact on Airbnb's market in Amsterdam. The supply-side metrics indicate a sharp decline in the availability of listings and hosts, especially for entire homes, which aligns with the regulatory restrictions. On the demand side, while overall tourist demand for Airbnb accommodations decreased, the occupancy rate remained relatively stable, suggesting that fewer listings were able to maintain high occupancy levels due to continued demand. Finally, the increase in average revenue per night, particularly for the treated group, suggests that scarcity driven by the 30-night regulation may have contributed to higher prices. These results highlight the complex interplay between regulatory interventions and market dynamics, emphasizing the need for further research into long-term effects and consumer behavior in the short-term rental market.

6. The Regression Analysis

Before delving into the specific regression analyses conducted in this study, it is important to provide a clear theoretical foundation. Econometrics is defined as the application of mathematical and statistical techniques to model and quantify economic relationships using real-world data. Through econometric tools, researchers can not only describe economic phenomena but also infer causal relationships between variables, making it a cornerstone of empirical economic research.

At the heart of econometrics lies regression analysis, a key technique used to estimate the relationships between dependent and independent variables. Regression models allow researchers to quantify how changes in one or more explanatory variables (independent variables) are associated with changes in an outcome (dependent variable). This helps test hypotheses about potential causal effects. The key idea is to examine if changes in a variable (e.g., the number of Airbnb listings) lead to measurable changes in economic outcomes such as local employment rates, property prices, or tourism revenue.

a. Theoretical Framework and Model Setup

In this study, the focus is on exploring the relationships between economic variables, such as the impact of Airbnb's presence on various economic indicators like online visibility, economic activity, and unemployment rates in different regions. The econometric analysis of causal effects is based on non-experimental, observational data, which reflects real-world behaviors and outcomes rather than being gathered from a controlled experimental setting.

Econometric data typically falls into three categories:

- Cross-sectional data: Data collected from multiple entities (e.g., individuals or firms) at a single point in time.
- Time series data: Data collected from a single entity over multiple time periods.

- Panel data: A combination of cross-sectional and time series data, where data is gathered from multiple entities over multiple time periods.

The dataset used in this study is the panel data, as it contains observations for each month from 2017 to 2023 for a variety of Airbnb properties within the city of Amsterdam. The dataset used is structured to have the listings that were active during the entire period. This type of data allows for more sophisticated econometric analysis, as it enables researchers to control for both individual-specific and time-specific factors.

The regression analysis aims to estimate the relationships between the variables using a mathematical model typically expressed as follows:

$$Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon_i$$

Where:

- Y_i is the observed value of the dependent variable at observation i,
- β_0 is the intercept (constant term),
- β_n represents the regression coefficients (slopes) associated with each explanatory variable X_n,
- ϵ_i is the error term, representing the discrepancy between the observed and predicted values and capturing unobserved factors that affect the dependent variable Y_i.

The parameters of the model (the betas) are typically estimated using the Ordinary Least Squares (OLS) method, which minimizes the sum of squared differences between the observed values of Y_i and the values predicted by the regression model. OLS provides a simple and effective way to estimate the linear relationships between variables.

While linear regression is useful for estimating relationships between variables, it has limitations when applied to panel data. In particular, it assumes that all unobserved factors (captured by the error term) are uncorrelated with the independent variables, which may not hold true when dealing with time-invariant characteristics in panel data.

To account for unobserved heterogeneity that could bias the results, Fixed Effects (FE) models are often employed. In contrast to simple linear regression, which assumes that the relationship between the independent and dependent variables is uniform across all observations, fixed effects models allow for entity-specific effects. This means that the model can control for unobserved characteristics that are unique to each entity (e.g., an individual Airbnb property), which remain constant over time but may influence the outcome variable.

The fixed effects model takes the form:

$$Y_{it} = \alpha_i + \beta X_{it} + \epsilon_{it}$$

Where:

- Y_{it} is the dependent variable for entity i at time t,
- α_i is the fixed effect specific to entity i (capturing unobserved, time-invariant characteristics),
- X_{it} represents the independent variables for entity i at time t,
- ϵ_{it} is the error term.

By including an entity-specific intercept α_i , the fixed effects model controls for any unobserved heterogeneity that is constant over time but varies across entities. This makes the fixed effects approach especially valuable in panel data studies like this one, where individual Airbnb properties may have unique characteristics (e.g., location, size, guest capacity) that affect their economic outcomes but do not change over time.

In practice, the choice between using a simple linear regression model and a fixed effects model depends on the nature of the data and the research question. If the goal is to control for unobserved, time-invariant characteristics, the fixed effects model is preferred.

However, if these characteristics are not a concern or if they do not correlate with the independent variables, linear regression may suffice.

Once the model parameters are estimated, it is important to assess how well the model fits the data. Two key measures are often used to evaluate the goodness of fit:

- Residual Standard Error (RSE): This measures the average distance between the observed and predicted values. A smaller RSE indicates that the model provides a better fit to the data.
- Coefficient of Determination R^2: This measures the proportion of the variability in the dependent variable that is explained by the independent variables. An R^2 value close to 1 indicates a good fit, meaning the model explains most of the variation in the data. Conversely, an R^2 close to 0 suggests a poor fit, which may be due to noise in the data or an incorrect model specification.

After evaluating the model's fit, the next crucial step is to test the statistical significance of the independent variables. In simple linear regression, the goal is to determine whether the independent variable X influences the dependent variable Y. In the case of multiple regression, the interest is in determining whether one or more independent variables have an impact on Y. This is done by testing the null Hypothesis $H_0: \beta_j = 0$ which states that the explanatory variable X_j has no effect on the dependent variable. The alternative hypothesis $H_1: \beta_j \neq 0$ suggests that there is a significant relationship.
To test these hypotheses, a significance level (commonly 0.05 or 5%) is first chosen. If the p-value obtained from the regression is lower than this significance level, the null hypothesis is rejected, indicating that the independent variable does indeed influence the dependent variable. Otherwise, the null hypothesis is accepted, suggesting no significant relationship between the variables.

By using regression analysis, this study aims to quantify the effects of Airbnb's entry into different type of listings and assess the impact of regulations on the four key dependent variables, based on the hypothesis formulated in the third chapter.

b. Results

This section presents the regression models used to assess the impact of the 30-day rental policy on various market outcomes in Amsterdam's short-term rental sector. Four key dependent variables were analyzed using Stata, each transformed into their logarithmic form to normalize the data: i) Available Nights, ii) People (Guests), iii) Occupancy Rate, and iv) Average Daily Rate (ADR).

The models include the following dummy variables:

- Treat: A dummy variable representing the listings subject to the 30-day limit (entire apartments, coded as 1 compared to those unaffected by the policy (rooms, coded as 0).
- Post: A dummy variable equal to 1 for observations recorded after the policy's introduction and 0 for the pre-policy period.
- Treat_Post: The interaction term between Treat and Post, which captures the differential impact of the policy on the treated group after its implementation.

Various control variables were included to account for both temporal and spatial variations:

- Time fixed effects (see Time FE column in the tables of results): they control month-by-month variations that could impact all Airbnb listings simultaneously, such as seasonal fluctuations, macroeconomic changes, or external shocks like the COVID-19 pandemic. Including these time effects ensures that the effects captured in the regression focus on the variation between the treated and control groups rather than being influenced by broader market trends.

- Airbnb listing fixed effects (see Airbnb FE in the tables of results): they control time-invariant characteristics of the properties, ensuring that the regression isolates the within-listing variation over time. This is crucial because different listings may inherently have different levels of attractiveness, location advantages, or amenities, all of which could affect their performance in the Airbnb market.
- Constant: In all models, a constant term (intercept) was included (see Constant row in the table results). This represents the baseline value of the dependent variable when all other predictors are zero.

Additional, in every model there are regression parameters, summarized below.

- N: This refers to the number of observations in the dataset used for the model (see N row in the table results). In every model analyzed the value of N is more than 800,000.
- R-squared (R^2): The R-squared statistic explains the proportion of variance in the dependent variable that is explained by the independent variables as mentioned before. This is expected to be lower when the model involves complex real-world data and social phenomena, and many external factors are influencing outcomes.
- Within R-squared: The within R^2 is particularly relevant for models with fixed effects. It shows the proportion of variance explained by the independent variables within the panel, after accounting for the fixed effects (e.g., listing-specific and time-specific characteristics).
- The p-values in the regression output are represented by asterisks in the table to indicate levels of statistical significance:
    - $p < 0.01$ (highly significant - represented with ***)
    - $p < 0.05$ (significant - represented with **)
    - $p < 0.1$ (marginally significant - represented with *)

  Asterisks denote the likelihood that the observed relationship between the independent variables and the dependent variable is not due to random chance.

Moreover, for each dummy variable in the model, the mean represents the average value across all observations (0 or 1), while the standard deviation indicates the extent of variation from the mean and it is represented in brackets.
The analysis used six models in total. Four of these (M1-M4) were selected as the most relevant for the analysis based on statistical significance and alignment with the research questions. Below are reported the explanation and the code in Stata for each model.

- Model 1 (M1): A basic model that includes only Treat, Post, and Treat_Post, without any fixed effects.

$$reghdfe\ \ Y\ \ treat\ post\ treat\_post, noabsorb\ \ vce(cluster\ ID).$$

- Model 2 (M2): Adds time fixed effects to control for broader time trends (month) that could influence all listings equally.

$$reghdfe\ \ Y\ \ treat\ treat\_post, absorb(ReportingMonth)\ \ vce(cluster\ ID)$$

- Model 3 (M3): Incorporates listing-level fixed effects to account for time-invariant characteristics specific to each Airbnb listing.

$$reghdfe\ \ Y\ \ treat\_post, absorb(ID\ ReportingMonth)\ vce(cluster\ ID)$$

- Model 4 (M4): Adds linear trends for treated listings to capture different underlying trends in the treated and control groups over time.

$$reghdfe\ \ Y\ \ treat\_post, absorb(ID\ ReportingMonth\ i.treat\#c.trend)\ vce(cluster\ ID)$$

Models M5 and M6 introduced additional neighborhood-level trends, but they were found to be less informative for this specific analysis and are not the focus here.
Now, the results for each dependent variable are presented in table form, including all relevant coefficients explained in the previous section.

i. Available Nights

The first dependent variable, log(Available Nights), examines the effect of the 30-day policy on the availability of Airbnb listings. Across all models, apparently the results seem contradictory but this is because of the different model used. However, in the M4, the most complete model, the effect of the regulation shows a negative and significant (-0.0613, $p < 0.01$) value of the coefficient treat_post. This number suggests that the policy ultimately resulted in a contraction of available nights for entire homes as hypothesized in the research questions.

Y = log(available days)	M1	M2	M3	M4
Treat	-0.2519705*** (0.0144259)	-0.2548509*** (0.0143244)		
Post	0.0554929*** (0.01414)			
Treat * Post	0.0897158*** (0.0169957)	0.128197*** (0.0163826)	0.0317305** (0.0158039)	-0.06133*** (0.0179768)
Constant	2.591282*** (0.0120147)	2.609345*** (0.0095206)	2.467006*** (0.0057952)	2.501131*** (0.006592)
Time FE	NO	YES	YES	YES
Airbnb FE	NO	NO	YES	YES
Treated Trend	NO	NO	NO	YES
N	830,134	830,134	825,591	825,591
R2	0.0056	0.095	0.522	0.5222
Within R2	0.0056	0.0949	0.4853	0.4855

ii. People (Guests)

For log(People), which measures the number of guests using Airbnb listings, the results show a decline after the policy implementation in M1, with the interaction term treat_post yielding a negative and significant coefficient (-0.1835, $p < 0.01$). This indicates a reduction in guest numbers for treated listings post-policy. However, in M3 and M4, after accounting for listing-specific trends, the sign flips, and the coefficient becomes slightly positive. This suggests that while there were fewer available nights, hosts concentrated bookings during periods of high demand, leading to more guests staying during those times.

Y = log(People)	M1	M2	M3	M4
Treat	-0.2804661*** (0.016321)	-0.2778472*** (0.0160942)		
Post	-0.1213504*** (0.0178873)			
Treat * Post	- 0.1834969*** (0.0207277)	- 0.2164895*** (0.0196326)	0.1063283*** (0.0168383)	0.0900165*** (0.0236569)
Constant	2.100143*** (0.014615)	2.176319*** (0.0114121)	1.868233*** (0.0061745)	1.874214*** (0.0086873)
Time FE	NO	YES	YES	YES
Airbnb FE	NO	NO	YES	YES
Treated Trend	NO	NO	NO	YES
Neighborhood Trend	NO	NO	NO	NO
N	830,134	830,134	825,591	825,591
R2	0.0145	0.0833	0.5285	0.5286
Within R2	0.0145	0.0832	0.4924	0.4924

iii. Occupancy Rate

The Occupancy Rate variable, representing the percentage of available nights booked, also shows interesting dynamics. In M1 and M2, the results indicate a slight decline in occupancy rates after the policy (with treat_post = -0.0399 and -0.05, respectively). However, in M3 and M4, once treated-specific trends are considered, the occupancy rate increases (0.0373, $p < 0.01$). This result aligns with the hypothesis that although fewer nights are available, those nights are more likely to be fully booked during high-demand periods. The values for occupancy positive and negative, even if significant, are low in every model (<5%).

Y = Occupancy Rate	M1	M2	M3	M4
Treat	-0.0140828*** (0.0041607)	-0.0132003*** (0.0041056)	N/A	N/A
Post	-0.0124946*** (0.004246)	N/A	N/A	N/A

Treat * Post	-0.0399271*** (0.0049145)	-0.050058*** (0.0047226)	0.0084216** (0.004281)	0.0373683*** (0.0050423)
Constant	0.4999217*** (0.0036061)	0.496961*** (0.0027776)	0.4664144*** (0.0015698)	0.4557998*** (0.001849)
Time FE	NO	YES	YES	YES
Airbnb FE	NO	NO	YES	YES
Treated Trend	NO	NO	NO	YES
Neighborhood Trend	NO	NO	NO	NO
N	830,134	830,134	825,591	825,591
R2	0.0043	0.1108	0.5239	0.524
Within R2	0.0043	0.1107	0.4874	0.4875

iv. Average Daily Rate (ADR)

The final variable, log(ADR), reflects the impact on the pricing strategy of hosts. The results from M1 show a significant increase in prices after the policy (treat_post = 0.2244, $p < 0.01$). This increase persists in M3 and M4, with the interaction term remaining positive and significant (0.1715, $p < 0.01$). The findings suggest that hosts responded to the reduced availability of nights by increasing their prices, particularly during peak periods, to maximize revenue.

Y = log(ADR)	**M1**	**M2**	**M3**	**M4**
Treat	0.0872601*** (0.0247527)	0.095981*** (0.0241843)		
Post	0.222649*** (0.0266337)			
Treat * Post	0.2244676*** (0.0315469)	0.2853254*** (0.0302395)	0.0005625 (0.0289079)	0.171579*** (0.0323769)
Constant	3.864876*** (0.0211086)	4.005685*** (0.0151984)	3.974714*** (0.0166004)	3.912003*** (0.0118725)
Time FE	NO	YES	YES	YES
Airbnb FE	NO	NO	YES	YES
Treated Trend	NO	NO	NO	YES
Neighborhood Trend	NO	NO	NO	NO
N	830,134	830,134	825,591	825,591

R2	0.0005	0.0633	0.4362	0.4364
Within R2	0.0005	0.0632	0.393	0.3931

The regression results clearly demonstrate that the 30-day rental policy had a significant impact on Amsterdam's short-term rental market. The results show a reduction in available nights and an increase in prices, consistent with the research hypothesis.

For Available Nights, the most complete model (M4) shows a negative and significant effect, confirming that the policy reduced the supply of available rental nights.

For People, the initial models indicate a decrease in guest numbers following the policy implementation. However, in the more complex models, with the inclusion of controls for listing-specific trends, the coefficient shifts slightly. This suggests that the minimal variations are likely due to the increased complexity of the model rather than a substantial change in the impact of the policy. Similarly, for Occupancy Rate, early estimates show a slight decrease, while the more advanced models indicate a modest increase. Since the coefficients are generally low, it is reasonable to expect small variations as more control variables are added, without altering the overall impact.

Finally, for ADR, the results consistently indicate an increase in prices after the policy, with positive and significant coefficients across all models. This suggests that hosts responded to the reduced supply by raising prices to compensate for the decrease in available nights.

In summary, the 30-day rental policy effectively reduced the supply of short-term rentals and led to higher prices. Model 4 (M4) stands out as the most accurate for this analysis, as it includes time and listing-specific fixed effects alongside linear trends for treated listings. This approach accounts for seasonal and property-specific variations, resulting in consistent findings of reduced available nights and increased average daily rates, supporting the hypothesized impact of the policy. Meanwhile, the minimal variations in guest numbers and occupancy rates are expected, given the small coefficients and increased model complexity.

7. Conclusion

The thesis has explored a complex and multifaceted topic: the impact of short-term rental regulations, with a specific focus on the 30-day limit imposed in Amsterdam. By analyzing Airbnb data from 2017 to 2023, the study investigated the dynamics triggered by these regulations within the short-term rental market, examining changes in property availability, demand, and pricing.

The hypotheses aimed to assess how the regulation affected the availability of Airbnb listings, the demand for these properties, and the daily revenues for hosts. Preliminary descriptive analysis has already shown a significant reduction in listings, particularly for entire apartments subject to the 30-day limit. Additionally, there has been an increase in average revenue per night, suggesting that the reduced supply created scarcity, driving prices upward.

Moving to the regression analysis, the findings revealed that the 30-day limit led to a clear reduction in available nights, as expected. This confirms the policy's success in restricting supply. The impact on ADR (average daily rate) was also significant, with prices rising consistently across all models, suggesting that hosts adjusted their pricing strategies in response to the reduced supply. For People and Occupancy Rate, while initial models showed a decline, the more complex models introduced slight positive shifts. However, the changes were minimal, likely due to small coefficient sizes and the added complexity of control variables. This shows that while availability was restricted, hosts capitalized on peak periods, optimizing their remaining availability to maintain or increase guest numbers and occupancy.

However, estimating the direct impact of regulations remains a significant challenge. While the literature provides numerous studies on the potential effects of short-term rental platforms and regulations, isolating the specific influence of local policies is complex. The short-term rental market is shaped by numerous variables, including global tourism trends, local economic conditions, and government intervention. Furthermore, the regulatory responses differ significantly from city to city, making it difficult to generalize the effects of regulation on a global scale. Each city operates within a unique context, and the effectiveness of regulations largely depends on the ability of local governments to implement and enforce the policies they adopt.

In conclusion, this research confirms that Amsterdam's 30-day rental limit effectively reduced supply and increased prices, while variations in guest numbers and occupancy were less pronounced, showing limited adaptability by hosts. These findings contribute to the broader understanding of the implications of short-term rental regulations and highlight the importance of local context in shaping policy outcomes.

a. Next Steps

Once conducted this analysis, the next steps could focus on assessing the long-term economic and social consequences of these regulations. One avenue for future research could involve exploring the broader effects on local businesses and housing markets over time. Understanding how the 30-day limit impacts neighborhood dynamics, local commerce, and the affordability of housing for residents would provide a more comprehensive understanding of the regulation's extended implications.

Another valuable direction could be to examine how short-term rental regulations influence the behavior of different types of property owners. For instance, are large-scale professional hosts adapting their strategies to maintain profitability despite the restrictions? Additionally, exploring whether certain hosts transition to offering long-term rentals as a result of the regulation could shed light on the policy's impact on alleviating housing shortages.

Finally, it may be worth investigating how the regulatory environment interacts with other factors, such as technological advancements in the sharing economy or the evolving nature of tourism post-COVID-19. These external trends could either amplify or mitigate the intended effects of local policies, adding another layer of complexity to understanding their overall impact.

A final point worth addressing is the situation in Italy, where tourism plays a crucial role in the economy. Similar debates around the impact of platforms like Airbnb have emerged in cities such as Rome, Florence, and Venice, which are facing increasing pressure on local housing markets due to the rise of short-term rentals. However, unlike Amsterdam, many Italian cities still have relatively underdeveloped or inconsistent regulatory frameworks. Recently, on 1st September 2024, Italy introduced the Codice Identificativo Nazionale (CIN), a mandatory identification code for all short-term rentals, overseen by the Ministry of Tourism. The CIN aims to centralize data on short-term rentals and enhance regulatory oversight across the country, providing transparency and reducing tax evasion. Despite this national initiative, implementation and enforcement remain inconsistent across regions, with some areas also maintaining their own regional codes, such as the Codice Identificativo Regionale (CIR) in Lombardia and Puglia.

This fragmented regulatory landscape creates uncertainty for property owners and residents, highlighting the need for a structured, city-specific approach that accounts for the unique characteristics of each city, rather than adopting a one-size-fits-all solution.

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9. Appendix

Appendix A: Effects of Airbnb Listings on Hotel Performance Metrics

This appendix summarizes the findings of three tables analyzing the impact of Airbnb listings on various performance indicators within the hotel sector:

Table 3: Effects of Airbnb Listings on Hotel Room Revenue (RevPAR). This table shows how different types of Airbnb listings (entire homes, private rooms, shared rooms) impact the average revenue per hotel room, taking into account factors like hotel supply, demand, and unemployment rates.

Table 3. The effects of Airbnb listings on Hotel Room Revenue (RevPAR).

	Total Airbnb Listings				Active Airbnb Listings			
	All Listings	Entire Homes	Private Rooms	Shared Rooms	All Listings	Entire Homes	Private Rooms	Shared Rooms
Log Airbnb Listingsrowhead	−0.031a (−3.25)	−0.030a (−3.09)	−0.027a (−3.01)	−0.012 (−1.08)	−0.023b (−2.48)	−0.025b (−2.41)	0.016c (−1.87)	−0.019c (−1.86)
Log Hotel Supplyrowhead	−1.25a (−12.87)	−1.27a (−13.33)	−1.25a (−12.74)	−1.35a (−14.01)	−1.28a (−13.00)	−1.27a (−12.64)	−1.31a (−13.45)	−1.33a (−14.12)
Log Employmentrowhead	2.08a (13.44)	2.02a (13.74)	2.09a (12.85)	1.81a (14.11)	2.01a (12.90)	1.99a (12.99)	1.95a (12.35)	1.80a (14.66)
Log Tourist Arrivalsrowhead	0.21a (13.67)	0.21a (13.69)	0.20a (13.26)	0.21a (12.94)	0.21a (13.61)	0.22a (13.59)	0.21a (13.41)	0.22a (13.39)
Unemployment Raterowhead	0.04a (10.28)	0.04a (10.31)	0.05a (9.93)	0.04a (10.18)	0.04a (10.05)	0.04a (9.99)	0.04a (9.62)	0.03a (10.45)
Constantrowhead	−15.93a (−4.59)	−14.72a (−4.46)	−16.02a (−4.41)	−9.66a (−3.31)	−14.21a (−4.03)	−14.08a (−3.98)	−12.72a (−3.60)	−10.04a (−3.69)
R-Squarerowhead	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83
Adjusted R-Squarerowhead	0.82	0.82	0.82	0.82	0.82	0.82	0.82	0.82
F-Testrowhead	61.95a	61.83a	61.78a	60.88a	61.45a	61.41a	61.15a	61.14a
Number of obs.rowhead	696	696	696	696	696	696	696	696

a, b and c denote 1%, 5% and 10% statistical significance levels, respectively. t statistics are in

Table 4: Effects of Airbnb Listings on Hotel Room Occupancy. This table examines the influence of Airbnb listings on hotel occupancy rates, distinguishing between different lodging types and analyzing external factors, such as tourist arrivals.

Table 4. The effects of Airbnb listings on Hotel Room Occupancy.

	Total Airbnb Listings				Active Airbnb Listings			
	All Listings	Entire Homes	Private Rooms	Shared Rooms	All Listings	Entire Homes	Private Rooms	Shared Rooms
Log Airbnb Listingsrowhead	−0.016a	−0.018a	−0.012a	−0.022a	−0.016a	−0.024a	0.008b	−0.017a
	(−3.57)	(−3.97)	(−3.00)	(−4.15)	(−3.60)	(−4.90)	(−2.16)	(−3.58)
Log Hotel Supplyrowhead	−0.03	0.03	0.02	0.04	0.03	0.07	−0.01	0.01
	(−0.67)	(0.72)	(0.47)	(0.89)	(0.76)	(1.60)	(−0.01)	(0.43)
Log Employmentrowhead	0.85a	0.85a	0.84a	0.77a	0.85a	0.90a	0.79a	0.73a
	(11.86)	(12.41)	(11.14)	(13.08)	(11.87)	(12.84)	(10.79)	(12.82)
Log Tourist Arrivalsrowhead	0.13a	0.13a	0.12a	0.14a	0.13a	0.13a	0.12a	0.13a
	(17.72)	(17.86)	(17.26)	(17.92)	(17.83)	(18.27)	(17.42)	(17.80)
Unemployment Raterowhead	0.02a	0.02a	0.02a	0.01a	0.02a	0.02a	0.01a	0.01a
	(9.11)	(9.43)	(8.61)	(9.56)	(9.26)	(10.02)	(8.38)	(8.98)
Constantrowhead	−16.53a	−16.49a	−16.21a	−15.37a	−16.66a	−18.16a	−15.02a	−14.28a
	(−10.20)	(−10.74)	(−9.54)	(−11.40)	(−10.16)	(−11.13)	(−9.09)	(−11.30)
R-Squarerowhead	0.70	0.71	0.70	0.71	0.70	0.71	0.70	0.71
Adjusted R-Squarerowhead	0.68	0.68	0.68	0.69	0.68	0.69	0.68	0.68
F-Testrowhead	29.57a	29.76a	29.33a	29.86a	29.58a	30.29a	29.06a	29.57a
Number of obs.rowhead	696	696	696	696	696	696	696	696

a, b and c denote 1%, 5% and 10% statistical significance levels, respectively. t statistics are in

Table 5: Effects of Airbnb Listings on Average Daily Rate (ADR) in Hotels. This table reports how Airbnb presence affects hotels' average daily rates (ADR), with breakdowns by type of listing and various economic indicators.

Table 5. The effects of Airbnb listings on Average Daily Rate (ADR).

	Total Airbnb Listings				Active Airbnb Listings			
	All Listings	Entire Homes	Private Rooms	Shared Rooms	All Listings	Entire Homes	Private Rooms	Shared Rooms
Log Airbnb Listingsrowhead	−0.001	0.003	−0.001	−0.002	0.004	0.011	0.004	0.006
	(−0.12)	(0.31)	(−0.18)	(−0.18)	(0.40)	(1.02)	(0.50)	(0.57)
Log Hotel Supplyrowhead	−0.98a	−1.01a	−0.98a	0.98a	−1.01a	−1.05a	−1.01a	−1.01a
	(−9.65)	(−10.05)	(−9.49)	(−9.72)	(−9.84)	(−9.94)	(−9.94)	(−10.31)
Log Employmentrowhead	1.91a	1.87a	1.92a	1.91a	1.85a	1.80a	1.85a	1.88a
	(11.76)	(12.09)	(11.23)	(14.27)	(11.37)	(11.22)	(11.17)	(14.65)
Log Tourist Arrivalsrowhead	0.14a	0.14a	0.14a	0.14a	0.14a	0.14a	0.14a	0.14a
	(8.64)	(8.57)	(8.65)	(8.24)	(8.46)	(8.24)	(8.65)	(8.24)
Unemployment Raterowhead	0.02a	0.01a	0.02a	0.02a	0.01a	0.01a	0.01a	0.01a
	(3.41)	(3.26)	(3.32)	(4.03)	(3.25)	(2.93)	(3.17)	(4.09)
Constantrowhead	−15.23a	−14.23a	−15.43a	−15.22a	−13.73a	−12.26a	−13.64a	−14.30a
	(−4.18)	(−4.11)	(−4.04)	(−5.00)	(−3.72)	(−3.31)	(−3.69)	(−5.03)
R-Squarerowhead	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91
Adjusted R-Squarerowhead	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90
F-Testrowhead	129.89a	129.91a	129.90a	129.90a	129.94a	130.12a	129.95a	129.96a
Number of obs.rowhead	696	696	696	696	696	696	696	696

a, b and c denote 1%, 5% and 10% statistical significance levels, respectively. t statistics are in

Appendix B: Additional Descriptive Analysis

Average of Reservation Days per Month: This chart shows the average number of reservation days per month, peaking in the summer months, which suggests higher tourist demand during that period.

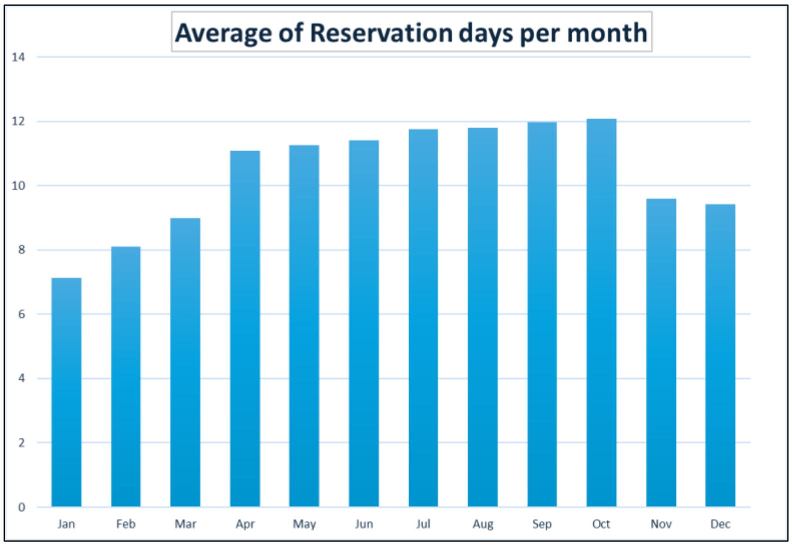

Figure a. Average number of reservation days per month, over the years 2017-2023

Number of Listings per Price Tier: This chart illustrates the trend in the number of Airbnb listings across various price tiers (budget, economy, luxury, etc.), indicating an overall decrease in listings from 2017 to 2023.

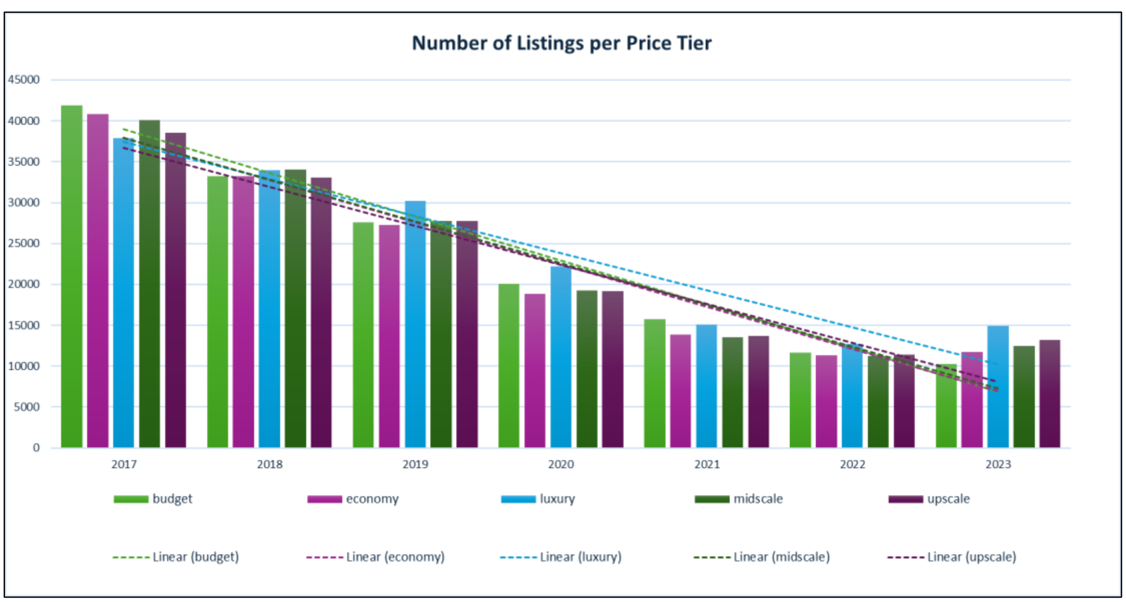

Figure b. Distribution of listings into 5 categories according to their price, over the years 2017-2023.

Average Minimum Stay Days: This chart displays the average minimum stay days required, showing slight variations between 2017 and 2023, with a peak in 2021.

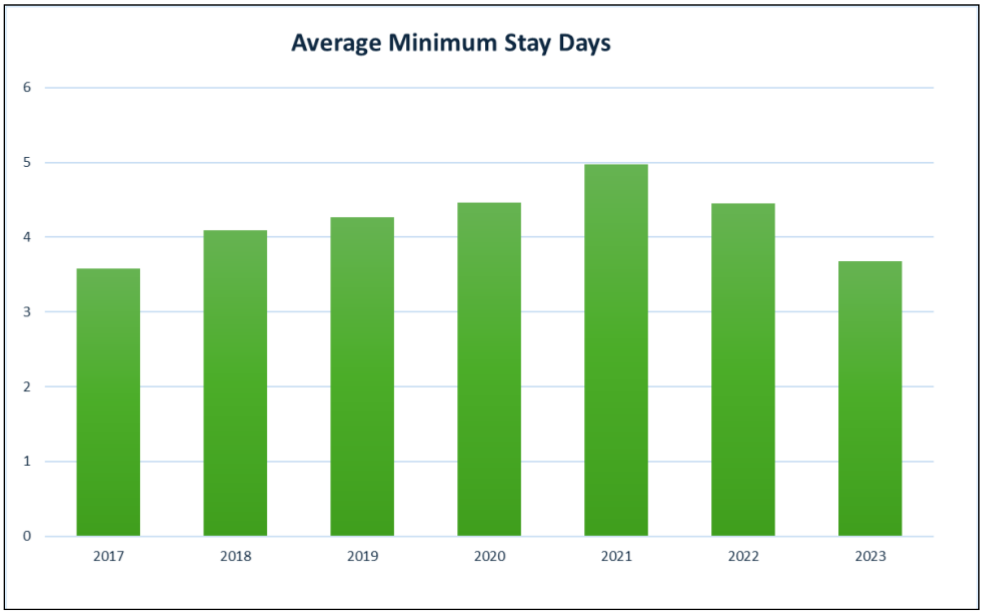

Figure c. Average minimum days of renting a property over the years 2017-2023.

Number of Airbnb Listings: This chart shows the change in the total number of Airbnb listings (broken down by category) from 2017 to 2023, highlighting a consistent decline over time.

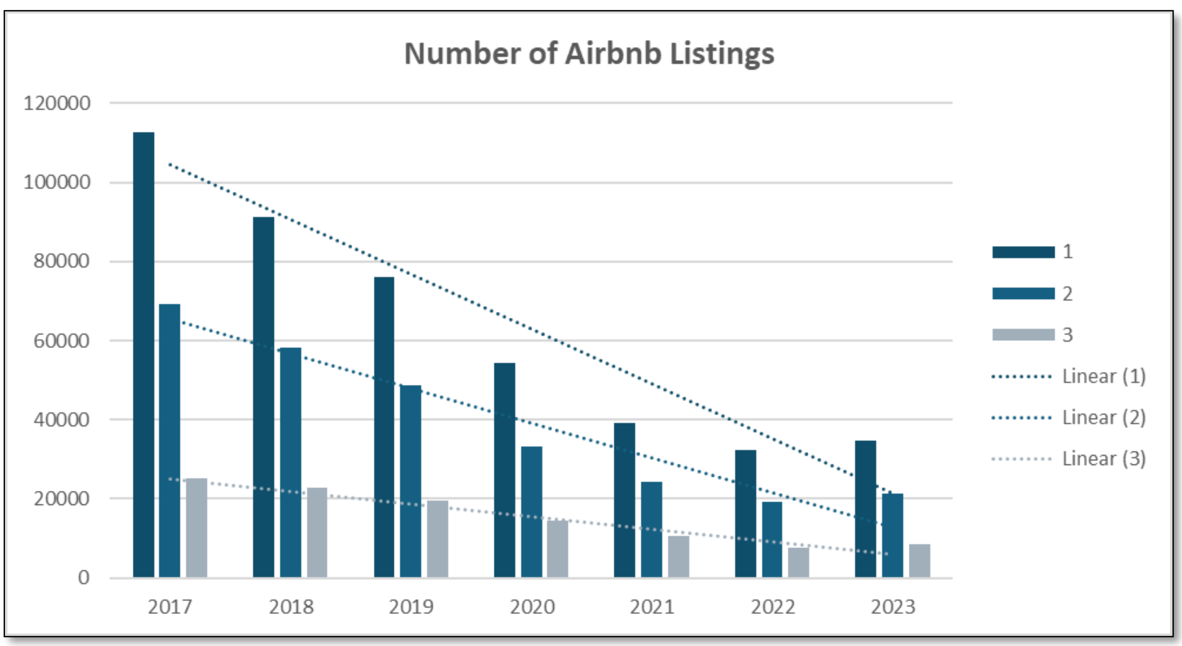

Figure d. Number of Airbnb listings over the years 2017-2023, divided per clustered Areas (1,2,3) based on their distance with the city center.

Appendix C: Airbnb's geographical distribution in the city of Amsterdam

This appendix presents two maps that illustrate the geographical distribution of Airbnb listings in Amsterdam:

- The first map highlights key points of interest and general areas where Airbnb listings are concentrated across the city.
- The second map provides a denser view of Airbnb listings, showing a more detailed distribution and concentration within various neighborhoods in Amsterdam.
-

These maps offer insight into the spatial presence of Airbnb accommodations within the city, illustrating areas with higher listing densities and proximity to major attractions.

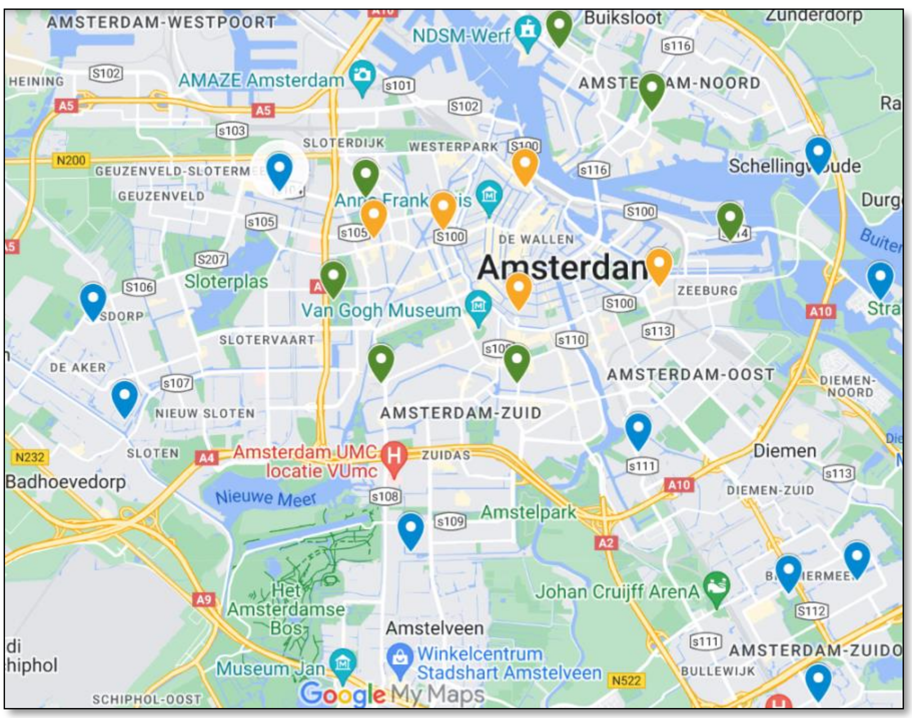

Figure a. Division of neighborhood into 3 areas based on their distance with the city center.

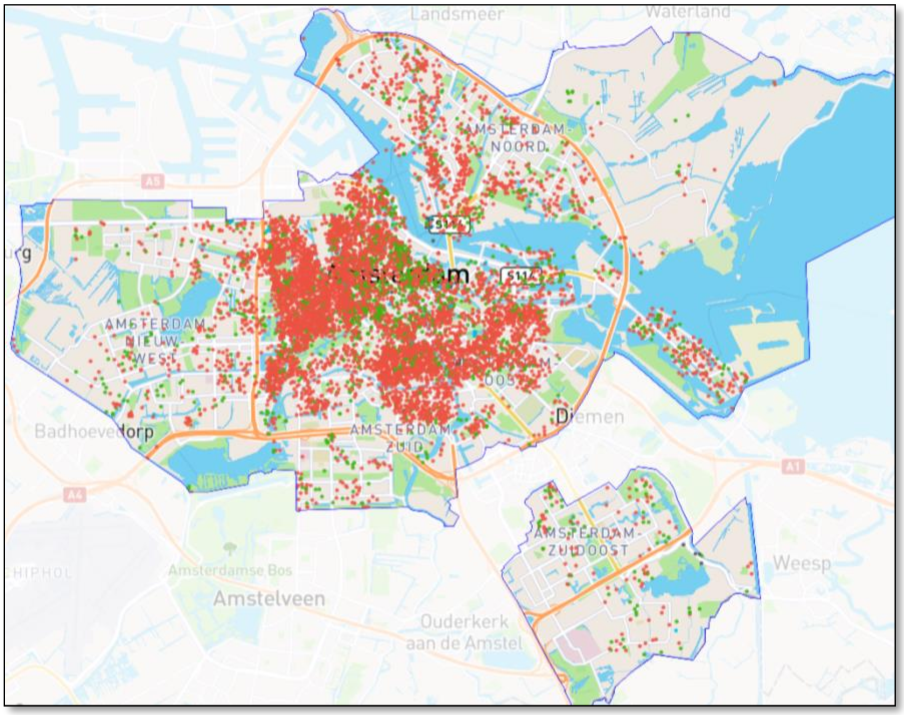

Figure b. Geographical distribution of Airbnb listings in Amsterdam.