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AIRBNB & ITALIAN VILLAGES: DO SHORT-TERM RENTALS HELP ECONOMY TO GROW?

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ABSTRACT

The spread of digital platforms and, at the same time, the birth of the so-called 'sharing economy' has profoundly impacted the society we live in. One of the sectors that has been most affected by these developments is certainly tourism, with Airbnb acting as the main character.
The purpose of this study is to analyze whether, in Italian villages, there is a positive relationship between the entry of Airbnb and the economic growth of the villages themselves. To develop this analysis, a panel dataset containing several information related to 269 Italian villages was used. The influences of Airbnb's entry on three different variables were analysed, one measuring the online visibility of these rural realities, one measuring the average income of the ordinary entrepreneur per capital in the village and one measuring the active population of the village.
The research techniques used were of two types. Firstly, a descriptive analysis phase aimed at carrying out preliminary analysis by means of which trends of the above-mentioned variables are identified within our sample. Subsequently, regression analysis, both simple and multivariate, were implemented for higher statistical significance.
What emerges from the studies is the positive relationship between Airbnb's entry into the villages and the three variables analysed. Greater statistical significance is present in the relationship of Airbnb's entry with both the online visibility of the village and its active population, as you can see from the p-values obtained.

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Introduction

In recent years, the beginning and the rapid growth of the sharing economy have changed the way individuals travel and find accommodation worldwide. Among the prominent players in this domain, Airbnb is one of the platforms that has gained significant traction. It connects travellers with unique lodging solutions and its birth contributed to reshape the tourism landscape. While numerous studies have explored the impact of Airbnb on urban centres and popular tourist destinations, a lack of research on which are its influence on the economy of small and traditional Italian villages is present in the literature.

Italy, mainly famous thanks to its cultural heritage, beautiful landscapes, and charming villages, has experienced an increase in number of tourists over the last few years. There is also a change in what tourists are mainly looking for, in fact they are increasingly search for authentic and immersive experiences. So, they are venturing beyond the well-known cities like: Rome, Florence, and Venice to explore the hidden treasures that are present within the Italian countryside. This shift in travel preferences has presented both opportunities and threats for the local economies of Italian villages.

The main objective of this master's thesis is to fill the existing research gap by examining the impact of Airbnb on the economy of Italian villages. More specifically, this study aims to investigate in which way the presence of Airbnb rentals in these rural areas influences various economic indicators, that could be local businesses, employment opportunities, housing market dynamics, and overall community well-being. Thanks to the use of robust statistical techniques, like descriptive statistics analysis and regression analysis, this research has the goal to provide quantitative evidence that can inform local communities, and tourism stakeholders in developing effective and sustainable strategies to speed up the development in this communities. Understanding which could be the economic implications caused by Airbnb in Italian villages has significant importance for different reasons. First, it allows us to assess whether the sharing economy model, which has been seen with its pros and cons in urban areas, results effective or not in the rural contexts. Second, it allows stakeholder to evaluate the potential benefits and challenges of Airbnb for local businesses, such as restaurants, shops, and artisans, which often form the backbone of village economies. As was outlined above, this study will investigate whether Airbnb listings are associated with influences on the economy. Moreover, another fundamental aspect that will be examined with the help of regression analysis is to understand if Airbnb has an influence on online visibility in Italian villages. The era we are living is full of digital platform that has changed the way of living of people and therefore, they have impacted travel and tourism patterns. So, try to understand which are the relations between Airbnb's presence and the online visibility of these villages is an aspect of crucial importance. This research aims to uncover empirical evidence and insights into whether Airbnb's listings affect the extent to which these villages are showcased and promoted through online channels, like for example their visibility on Google.

Furthermore, this research has the objective to investigate the effects of Airbnb on employment opportunities in Italian villages. Tourism-related services have the potential to create new jobs or transform the nature of existing employment. This study will explore the relationship between Airbnb activity and employment figures, shedding light on whether short-term rentals contribute to job creation, local economic diversification, or potential displacement of traditional occupations.

Chapter 1: General Context

1.1 What is sharing economy?

The sharing economy is often seen as an answer to the several limitations that the traditional economic systems have. In fact, it is frequently described as inefficient, wasteful, and exclusionary. The sharing economy enables a more flexible and collaborative approach to economic activity, due to the fact that allows individuals and businesses to share resources. It gives the possibility to ensure the access to resources on a more affordable basis. This can be of great benefit to those who have limited funds or live in particularly expensive areas. Besides its economic benefits, the sharing economy has also been recognised for another reason: its environmental and social advantages. Thanks to the promotion of the sharing and reuse of resources, it can help in the reduction of waste and in the lowering of carbon emissions. A further point in favour of the sharing economy is its potential to foster social inclusion, as people from different backgrounds can come together and work towards a common goal. Obviously, this economic model also has some threats that are appropriate to be presented. One of the biggest issues is regulation, as the existing regulatory frameworks are often ill-suited to deal with the complex and rapidly evolving nature of sharing economy platforms. There could be also problems related to safety and labour rights, in fact many sharing economy workers are classified as independent contractors and therefore, they are not entitled to the same protections as traditional employees. It is expected that regulatory steps will be taken in the coming years to ensure that the sharing economy operates in a fair and sustainable manner.

Despite these difficulties, the sharing economy does not stop and continues to grow and evolve, with the birth of new platforms and services This type of economy is destined to become an integral part of our future in the coming years even more than it already is today. Precisely for this reason, it is of paramount importance to understand the benefits and pitfalls that can arise from it.

1.2 Example of a Sharing economy Platform: Uber

Uber is definitely one of the most well-known examples of the sharing economy, and its success has played a significant role in making the concept better known among the population. It is a platform that connects drivers with passengers through a mobile app. In fact, customers can indicate a point of departure and an arrival point and search for a person who can take them from one point to another by a vehicle. The platform ensures that the driver can use his or her personal vehicle and the passenger using the application must set up the ride details. Based on the available drivers in the proximity, the software contacts one of them, who is close to the departure point chosen by the passenger and can accept the ride requested by the person needing the lift.

The main reason because Uber is related to the sharing economy is through the sharing of resources, in this case the resource is the vehicle. In fact, rather than owning a car, passengers can simply request a ride when they need one, and drivers can use their personal vehicles to provide those rides. This allows drivers to earn money by sharing a resource they already have, and passengers to access a convenient and affordable transportation option.

Another way in which Uber embodies the sharing economy is through its use of technology. It is an app-based platform, and it allows for an efficient matching of drivers and passengers. It also provides information on the availability of drivers and on price of the ride, both two features can change in real time depending on the situation between supply and demand at that specific moment. The technology helped a lot to make ride-hailing more accessible and user-friendly giving the possibility to Uber to expands its services very rapidly in different cities around the world. At the same time, the spread of Uber has also raised questions about the impact that the sharing economy has on traditional industries and its relationship with the employment. Clearly, the sector that has been most impacted by the rise of this ride-sharing platform has been the taxi industry. This has led to several debates on the regulation of this service and the fairness of competition between traditional taxi drivers and Uber drivers, in fact in some states including Italy Uber is still not too widespread. There are also concerns about the labour practices of Uber and other sharing economy platforms. As mentioned above, many drivers are classified as independent workers rather than employees, which means that they do not enjoy the same rights and protections as traditional employees. In fact, more regulation and supervision of these platforms is expected in the coming years to ensure fair treatment of workers and protection of labour rights.

Overall, the example of Uber shows which are the potential benefits and challenges of the sharing economy. Even if it has provided a convenient and affordable transportation option for millions of people, it has also raised important questions about regulation, competition, and labour rights. As the sharing economy continues to grow and evolve, but it will be important as well to address these issues in a way that promotes fairness, sustainability, and economic opportunity for all.

1.3 Airbnb

Airbnb, which will be a pivotal element of our analysis, is another of the most famous sharing platforms that have emerged in the 21st century and has become a major player in the tourism industry. Indeed, Airbnb is an online platform that allows people to rent out their homes, rooms in their flats or other properties to travellers seeking short-term accommodation.

Airbnb is considered a sharing economy platform because it allows individuals to share their homes and other properties with others. In fact, hosts, thanks to the rent of their unused space, they are able to earn extra income and exploit a resource they already have, at the same time travellers can find a unique and affordable accommodations in several locations around the globe.

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, 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.

At the same time, the growth of Airbnb has raised concerns about the impact on both the availability and influence of housing prices in certain areas. Common thinking is that Airbnb can drive up housing prices and contribute to the displacement of long-term residents, particularly in areas with high demand for short-term rentals.

In this thesis, an in-depth literature review will analyse whether there are students who prove these theories, trying to enrich the literature where there are gaps.

1.4 Online Visibility

At the core of online visibility lies the concept of "being seen" in the vast ocean of digital information. When a website, business, or individual enjoys high online visibility, it means they have succeeded in making themselves noticeable and accessible to their target audience. This prominence is not a matter of chance but rather a result of strategic efforts to optimize their online presence. Search engines, social media platforms, and other digital channels act as gateways to the vast virtual world, and those who understand the mechanics of these gateways are better positioned to enhance their visibility. Search engine optimization (SEO) is one of the most critical elements in achieving online visibility. It involves fine-tuning a website's structure, content, and keywords to align with search engine algorithms, thereby improving its ranking in search results. Appearing on the first page of search engine results dramatically increases the likelihood of users clicking on a link, driving more organic traffic to the website. In addition to SEO, content marketing plays a significant role in boosting online visibility. Creating valuable, relevant, and engaging content not only attracts users but also encourages them to share it with their networks. This user-generated sharing extends the reach of the content, exposing it to new audiences and increasing its visibility across various online platforms. Social media marketing is another powerful tool for enhancing online visibility. With billions of active users on social media platforms, businesses and individuals can connect with their target audience directly. By crafting compelling social media campaigns, sharing engaging content, and interacting with followers, they can increase brand awareness and draw more users to their websites or profiles. Furthermore, online advertising, such as pay-per-click (PPC) campaigns, sponsored posts, and display ads, can be instrumental in boosting visibility by reaching a broader audience and driving targeted traffic to specific web pages. For businesses, online visibility is crucial for building brand recognition, attracting potential customers, and ultimately driving sales. In connection with our analysis, online visibility is of great importance for small Italian villages as it plays an important role in several aspects of their life and development. It enables them to promote tourism and attract visitors, contributing to the local economy and the growth of business activities. Moreover, online visibility helps to preserve and promote the rich cultural and historical heritage of these villages, helping to keep their identity alive. It also promotes sustainable development by encouraging responsible tourism practices and can attract investment to improve the infrastructure and quality of life in small villages. In an increasingly connected world, online visibility is an essential tool to ensure the well-being and prosperity of these rural communities.

1.5 Italian Villages: definition

The analysis that will be developed in the thesis will aim at measuring the impact of Airbnb on the economy of the Italian villages. Therefore, the definition of Italian villages is key to understand a crucial element of the study.

A village refers to a small settlement or community, often found in rural areas, that typically has a smaller population compared to a town or a city. It is characterized by its close-knit community and often retains a traditional or historical atmosphere. It is common to find a central core or square in a borgo, where houses, shops, and other essential services are located. This central gathering point often serves as a hub for social interaction and community events. In terms of size, a borgo is usually smaller than a town or city but larger than a single isolated dwelling. It is a cohesive unit that may have its own unique cultural identity, local traditions, and historical significance.

Villages can vary in their specific features and architectural styles depending on the region or country. Some may have narrow winding streets, while others might have a more structured layout. In many cases, they are characterized by their picturesque charm, with well-preserved buildings, historic landmarks, and natural surroundings that contribute to their appeal.

Chapter 2: Theory Background

2.1 Literature Review

The literature analysis was conducted to identify whether or not there is a gap presented in it regarding precisely the analysis of the impact of Airbnb or other sharing platforms on villages. As it was possible to examine from the research, most of the studies focus on the impact of so-called sharing platforms on large cities while papers considering villages were not found.

In recent years, the rise of sharing platforms has significantly transformed the economic landscape, reshaped traditional industries, and created new opportunities for individuals to participate in the economy. These platforms, facilitated by technology and fuelled by the principles of collaboration and access over ownership, have disrupted sectors ranging from transportation and accommodation to labour and services. The impact of sharing platforms on the economy has been profound, influencing employment patterns, consumer behaviour, and market dynamics.

A platform in order to be considered as sharing platform it needs to have several characteristics, such as:

1. ***Peer-to-Peer Transactions:*** they facilitate direct transactions between individuals, allowing them to share or exchange resources, services, or assets without the need for intermediaries. The platform acts as a digital marketplace that connects providers and users, enabling individuals to interact and transact directly with each other.
2. ***Access over Ownership:*** they emphasize access to goods or services rather than ownership. They enable individuals to access and utilize resources or assets temporarily or on-demand, promoting a more sustainable and efficient use of existing resources.
3. ***Underutilized Assets:*** they leverage the underutilized capacity of assets. They allow individuals to monetize their idle resources or assets, such as spare rooms, vehicles, tools, or even skills, by making them available to others when they are not in use.
4. ***Technology-enabled Matchmaking:*** they utilize technology, particularly online platforms and mobile applications, to connect providers and users. They employ algorithms and user profiles to facilitate efficient matchmaking, ensuring that individuals can find and connect with the most suitable resources or services.
5. ***User Ratings and Reviews:*** they often incorporate a reputation system that enables users to rate and review each other based on their experiences. These ratings and reviews help

build trust and confidence among participants, facilitating more reliable transactions within the platform.

6. ***Trust and Safety Mechanisms:*** they implement various mechanisms to establish trust and ensure the safety of participants. These mechanisms may include identity verification, secure payment systems, insurance coverage, and dispute resolution processes to mitigate potential risks and conflicts.
7. ***Community and Social Interaction:*** they often foster a sense of community and encourage social interaction among participants. They provide avenues for communication, collaboration, and the formation of networks, enhancing the overall user experience and creating a sense of shared ownership.
8. ***Disruption of Traditional Industries:*** they have disrupted traditional industries by offering alternative ways to access goods and services. They have challenged traditional business models, such as hotels, taxis, or retail, by providing more affordable, flexible, and personalized options to consumers.

Over 25 articles were collected, following a research strategy that aimed at founding before papers regarding the effects of sharing platform on the economy and then more specifically searching the impacts of Airbnb. Once founded a sufficient number of articles they were then divided into the following four topics:

- Impact of the sharing platforms on economy
- Impact of Airbnb on hotel
- Impact of Airbnb on housing prices
- Impact of Airbnb on social community

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

2.1.1 Impact of the sharing platforms on economy

As has been pointed out in the previous section, the impact that sharing platforms have on the economy is often disruptive. Sharing platforms, as outlined in the previous paragraphs, refers to a peer-to-peer exchange of resources performed through the use of a digital tool. One of the principal expectations that comes from these exchanges of resources is the possibility for both the providers and the user of obtaining new monetary benefits (Vaughan, 2016). Providers of sharing platforms derive benefits from the opportunity to earn additional income by monetizing their housing, tools, resources, time, and skills. On the other hand, consumers benefit from the ability to access goods and services without the need for outright ownership, as well as the competitive pricing offered by platform-mediated transactions (Artioli, 2018).
In the literature, however, there are conflicting studies regarding the benefits brought to the economy by these platforms. One perspective highlights the efforts of prominent platforms to generate reports demonstrating the economic advantages experienced by providers. Notably, a study conducted by Hall and Krueger at the behest of Uber revealed that drivers on the platform highly valued the flexibility associated with their job and earned at least comparable, if not higher, incomes than traditional U.S. taxi drivers (Hall and Krueger, 2015). Moreover, the impact of monetary benefits can be analysed in relation to how they influence the distribution of income among various socio-economic groups. The changes in consumption patterns are particularly noticeable among users with incomes below the median, who also contribute a significant portion of the rental supply. This indicates that individuals with below-median income can consistently benefit from a significant share of the advantages derived from peer-to-peer exchanges of this nature (Fraiberger and Sundararajan, 2015). On the other hand, the opposite view states that peer-to-peer exchanges help to reinforce inequalities between the different levels of the population. Distribution of income within the bottom 80% of population is affected by these peer-to-peer exchanges, in fact there is a less evidence that working classes is benefiting from these platforms. This is due to the fact that with the invention of these sharing platform, there is a huge possibility that more wealthy families will move into businesses that traditionally belonged to less ones, impacting on their earnings and increasing inequality (Schor, 2017).

There is a specific type of sharing platform economy called *gig-economy platforms.* They are characterized by their utilization of online platforms to connect individuals seeking services with those offering them, while positioning themselves as intermediaries rather than service providers. These services can encompass both online tasks like photo tagging or survey completion, as well as offline services such as housecleaning or transportation.

As gig businesses categorize the individuals that provide services as independent contractors, they assert that they do not establish an employer-employee relationship and therefore are not obligated to comply with labour laws. Consequently, they generally do not offer benefits like health insurance or workers' compensation. Notably, unlike traditional independent contractors, gig workers typically do not have the ability to negotiate their rates or contractual terms, but instead must electronically accept the platform's terms to access available assignments (Tran, 2017).

In literature, the impact of gig-economy platform has been assessed on the entrepreneurial activity through an analysis (Burtch, 2018). Entrepreneurship relies on the presence of surplus resources, known as "slack resources," which can be redirected towards entrepreneurial pursuits. Gig economy platforms, with their claimed benefits of flexible scheduling and steady income for service providers, have the potential to facilitate the strategic reallocation of limited resources, such as time, allowing aspiring entrepreneurs to advance their budding ideas. Moreover, entrepreneurs can be encouraged to explore and exploit new opportunities as they emerge.

When considering the impact of gig-economy platforms on entrepreneurial activity, an intriguing dilemma emerges. On one hand, the availability of gig-economy employment may equip individuals with the flexibility and resources needed to pursue new ventures, potentially leading to an overall increase in entrepreneurial activity. Conversely, the presence of gig-economy platforms might serve as an appealing employment option for individuals who would have otherwise become necessity-based entrepreneurs, potentially resulting in a reduction in total entrepreneurial activity.

In this study, two measures are used to quantify entrepreneurial activity, the first is the number of crowdfunding campaigns that are launched on Kickstarter while the second metric is based on the number of self-employed people in each location considered. These two measures are strongly complementary as through the first measure about Kickstarter it gives us information about entrepreneurial activity at the project level and about people who are also engaged in paid work by companies. The second only captures those who make entrepreneurial activity their first job. The independent variable used in this regression analysis is the revenue of Uber X. While the two dependent variables used in the two studies are the two previously mentioned metrics, number of Kickstarter campaigns launched in that month in the reference area and number of self-employed individuals in that month in the reference area.

By employing a multi-treatment, difference-in-difference approach focused on the entry of Uber X, a gig-economy platform, the study reveals consistent evidence indicating a negative effect of gig-economy platform entry on entrepreneurial activity. This is evident through a decline in the volume of crowdfunding campaign launches and individuals reporting self-employment in the U.S. Census Bureau's Current Population Survey. Moreover, the study finds that the entry effect is more pronounced when the entering platform has lower fixed costs of participation (e.g., comparing Uber X and Uber Black). The observed impact primarily manifests as a decrease in unsuccessful crowdfunding campaigns and unincorporated self-employment, indicating a decline in the presence of lower-quality entrepreneurs. These findings suggest that gig-economy platforms provide necessity-based entrepreneurs with an alternative and preferable employment option.

2.1.2 Impacts of Airbnb on Hotel

In this and the following paragraphs, it will be discussed in more detail what impact Airbnb's entry has had on the economy. In the following we will analyse the effects of Airbnb's entry into an area on its hotels. It worth to be mentioned that all the papers founded in literature they are strictly related to examinate the effects of Airbnb in major cities around the globe.

In order to measure the degree of Airbnb's influence in the principal hotel markets, were used three measure key performance metrics (Dogru, 2018):

- RevPAR, hotel revenue per available room.
- ADR, average daily rate.
- OCC, occupancy rate.

In the four hotel markets chosen (London, Paris, Sidney, and Tokyo), where performed a least ordinary square regression analysis that showed an identical result in all the different markets. The findings indicate a substantial year-over-year growth of over 100% in Airbnb listings within these prominent cities. Furthermore, the impact of Airbnb on hotel revenue per available room (RevPAR) and occupancy (OCC) is both negative and statistically significant. Specifically, an increase of 1% in Airbnb listings corresponds to a decrease in hotel RevPAR ranging from 0.016% to 0.031% in these specific hotel markets.

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 parenthesis.

Figure 1 Effects of Airbnb listings in the four hotel markets chosen on Hotel Room Revenue

As showed by the previous study, the impact of Airbnb in the four hotel markets chosen seems to be negative.

The influence on the existing hotel industry is a significant consideration since tourism plays a crucial role in the economy. Hotel industry professionals argue that Airbnb creates an uneven playing field by enabling hosts to evade the taxes and regulations imposed on formal hotel establishments. This perceived advantage allows Airbnb to expand the availability of short-term accommodations, directly competing with traditional hotel rooms.
Despite these complaints from those in the tourism industry, there are some studies in literature that tend to state the opposite as it seems that Airbnb has a positive impact on the hotel sector. In the paper "Understanding Airbnb in fourteen European cities" (Yeung, 2018), a regression analysis was performed considered as independent variable the number of Airbnb listings in a city, as dependent variable the different hotel performances (Rev, OCC, ADR) and as control variables the log of population and the unemployment rate. The following linear regression equation has been used:

$$HotelPerformance_{it} = \beta Airbnb_{it} + \delta_i + X\gamma + \varepsilon_{it}$$

The findings reveal a positive impact of Airbnb activities on hotel performance. Utilizing the second method of time detrending, a 10-percentage point rise in Airbnb listings corresponds to an average increase of 5.7 percentage points in hotel occupancy rate. However, the same increase in Airbnb listings leads to a marginal rise of 0.15 percentage points in average daily rate (ADR) and a slight increase of 0.27 percentage points in total revenue. As anticipated, the regression models indicate a negative relationship with the unemployment rate. While population does not exhibit a significant influence on ADR and total revenue, it displays a negative correlation with occupancy rate.

Table 4 : Baseline Estimation

	1	2	3	4	5	6
	Occupancy		ADR		Revenue	
Airbnb	.820	.570*	.030**	.015**	.042**	.027***
	(1.62)	(2.10)	(2.30)	(2.75)	(2.28)	(3.78)
Unemployment	-.349***	-.405***	-.020***	-.023***	-.025***	-.029***
	(-3.14)	(-4.23)	(-3.17)	(-3.48)	(-3.63)	(-4.25)
Population	-87.6*	-85.1*	-.566	-.414	-1.86	-1.69
	(-1.83)	(-1.89)	(-.53)	(-.39)	(-.90)	(-.84)
Time FE	Y	N	Y	N	Y	N
Month FE	N	Y	N	Y	N	Y
Linear Trend	N	Y	N	Y	N	Y
No. of Obs.	2122	2122	2122	2122	2122	2122
Within R-sq	.619	.569	.411	.332	.606	.551
Between R-sq	.193	.193	.467	.446	.796	.798
Overall R-sq	.019	.020	.246	.224	.704	.705
Robust SE are computed and t-statistics are shown in parentheses.						
* p<10% ** p<5% *** p<1%						

Figure 2 Regression analysis results of Airbnb's effects on hotel performances in 14 European Cities.

But the impact of Airbnb was not only analysed from the point of view of hotel performance. An attempt was made to understand the portion of customers that Airbnb takes away from the hotel market. In the US in 2016, it was about 1.4 per cent the amount of hotel demand that was represented by Airbnb demand (Lane and Woodworth, 2016), with a larger footprint in major urban centres, but this percentage is sure to rise over the years. The researchers conclude suggesting that the main impacts that Airbnb will create on hotel in the future will be that amount of prices during the tourism peak periods will be influenced. In fact, as can be imagined, if we increase the competition in a sector we need to lower or keep the same prices to stay competitive. The second cause that the growth of Airbnb could create is the reduction of traditional hotel construction and therefore, prevent the risk of overbuilding.
"But is Airbnb really being used as a substitute for hotels? And if so, which types of hotels tend to be most affected by Airbnb's entry into a specific city?"
A study was found in the literature that precisely aimed to investigate how many customers used Airbnb as a substitute for hotels. The data collection was conducted from July 2015 to

October 2015 and involved 800 users of the Airbnb service in major Canadian cities. These people completed an online survey, which was created ad hoc to allow once all responses had been collected, to carry out an analysis aimed mainly at answering the two questions mentioned above (Guttentag, 2017).
Almost two-thirds of the respondents stated that they have used Airbnb as a substitute for hotel. In addition to this percentage, to understand in which categories of hotel Airbnb is more a threat the following three hotel categories were analysed in more detail:

- **Budget hotels:** they are small to midsize property that offer basic facilities and services for a low price.
- **Mid-scale hotels:** they are limited services hotel that offer comfortable room that provide a safe accommodation for a price-range that is on average.
- **Upscale hotels:** they are hotels that offer luxury amenities and a full accommodation with a high level of personalized service.

Almost 70% of the respondents indicated that they would have stayed in a mid-range hotel. This result might be explained due to the fact that Airbnb mid-range normally fall in a similar price range as many Airbnb listings, making them more comparable options for travellers seeking an affordable accommodation.
Airbnb not only has an impact on hotel room prices but also has an influence on hotel share prices (Teitler-Reglev, 2022). The aim of the study is to identify whether the digital platform's advertisements influence hotel share prices, but not only. In addition, the impacts caused by the tone of the message (positive or neutral) and the target audience (family, youth or adults) are also evaluated. Based on the first hypothesis that the researchers wanted to test, the release of announcements on Airbnb's platform has an impact on the stock prices of hotels. Investors who have access to this information before it becomes public can potentially use it to generate abnormal returns. Moreover, results provide support for the argument that Airbnb serves as a substitute for traditional hotels, as these announcements negatively affect the value of hotel stocks.
Furthermore, the findings also confirm the second hypothesis regarding the tone of the Airbnb announcements. In fact, the tone, whether positive or neutral, had differing effects on hotel stock prices. Specifically, when positive information was conveyed in the Airbnb announcements, investors responded by short-selling hotel company stocks. However, when the announcements were neutral, investors did not exhibit any notable response as they did not anticipate any significant changes.

Lastly, results are aligned with the third hypothesis as well, which proposed that the targeted audience in the announcements (families, young people, or adults) would influence hotel stock prices. Announcements tailored for young people had no discernible impact on hotel company stocks, possibly because this demographic group tends to utilize hotels less frequently and opt for more affordable accommodation options. On the other hand, announcements targeting families had the longest-lasting effect, spanning four days prior to the announcement and eight days afterward. This outcome can be attributed to the fact that families are typically the group that spends the most on hotel stays. As for announcements targeting adults, their effect commenced on the day of the announcement and persisted for the subsequent eight days.

2.1.3 Impacts of Airbnb on housing prices

In current literature, the topic that is most discussed in relation to Airbnb is certainly the impact it has on the prices of house rentals and property sales. Based on theoretical considerations and empirical findings, it is anticipated that cities with a significant presence of Airbnb will experience higher prices for rental accommodations and housing. This can be attributed to the assumption that a portion of available units has been taken out of the rental housing market, creating an artificial sense of scarcity. Moreover, the cost of housing is expected to rise as the presence of the homestay platform increases the opportunity cost associated with not purchasing a property. This is due to the attractiveness of earning returns through Airbnb rentals, which incentivizes individuals to invest in real estate. Housing is a basic human necessity (Sridhar, 2022), India in the last years with an impressive growth of the population is facing a severe rental housing crisis. Indian cities are the focus of the study realized by Sridhar; the researcher wanted to assess the impact of Airbnb in the Indian rental market.

He divided the houses based on the number of rooms, including one, two, and three-bedroom apartments and then he took into account the potential endogeneity of Airbnb density. The findings indicate that the density of Airbnb listings has a significant impact, leading to higher rents for apartments of various sizes and an overall increase in housing prices. Based on the estimates, a 1-percentage-point rise in Airbnb density corresponds to an approximate increase of 0.08% in the rent of two-bedroom apartments, 0.14% in the rents of three-bedroom apartments, and 0.39% in housing prices per square foot.

In addition to the study carried out on Indian cities, there are others in the research concerning the European market. Interesting is the paper 'Does Airbnb Disrupt the Private Rental Market?

An Empirical Analysis for French Cities' (Ayouba, Breuillé, Grivault, and Le Gallo, 2019), where the French rental market is analysed. In this country, Airbnb has the largest presence only behind the United States and Paris, one of the cities studied, is the city with the most Airbnb listings.
The findings are interesting, as a matter of fact it is found that the presence of Airbnb rentals does not uniformly cause an increase in private-sector rents. The research reveals that in Lyon, Montpellier, and Paris, a one-point rise in the density of Airbnb rentals leads to rent increases of 0.3851 percent, 0.3982 percent, and 0.5242 percent, respectively. Further investigation demonstrates that professional Airbnb rentals, operated by hosts with multiple lodgings or over 120 days of reservations per year, have a greater impact on rents in Paris, with an increase of 1.2372 percent, while no longer affecting Lyon and Montpellier. However, the effect of Airbnb rentals becomes significant in Marseille. These results are even more pronounced when considering new rental agreements exclusively. While there are some slight variations in the cities with significant coefficients depending on the density definition (all Airbnb renters versus professional renters only) and the sample (entire dataset versus new rental agreements), Paris consistently emerges as the city where Airbnb rentals have a significant effect on private rents. The study also reveals that the impact of Airbnb activity on rents in Paris and Montpellier intensifies as the proportion of owner-occupiers increases and declines with higher hotel density. The presence of second homes has contrasting effects in Paris and Montpellier, reducing the marginal effect of Airbnb activity in Paris but increasing it in Montpellier. Accounting for spatial differences, these results highlight the necessity of implementing distinct regulations tailored to specific cities, as Airbnb activity has no impact on rents in some locations while causing increases of up to 0.52 percent in others. By identifying the role of the "professional" Airbnb business, particularly in Paris, which disrupts the private rental market more significantly, this study supports the need for stricter regulations to prohibit professional activity, as set forth in the ELAN legislation passed in 2018.
What can be understood from this study is how it is perhaps not possible to argue that there is a general law governing Airbnb's influence on rental prices. The impact of the digital platform is likely to be city-specific, in fact there are many other economic and demographic factors that have an impact on the cost of a rental. What emerges strongly from the study is that in Paris, the most populous city and the one with highest number of tourists per year among those analysed, Airbnb rentals always have a significant effect on private rents.
Consequently, in order to find out whether this was a singular fact or not, other studies were sought in the literature today that take into consideration populous and very touristic cities.

A first study found concerns the city of Los Angeles (Koster, Ommeren & Volkhausen, 2018), where the overall impact of both Airbnb and home-sharing organizations (HSOs) on average property prices in LA County was analysed. To achieve this, estimates were combined with descriptive data on house prices and the number of listings in various areas, allowing to assess the total effects on property prices at both the county level and specific locations within LA County.

Based on our estimates, the overall gains of Airbnb for LA County are relatively modest at 3.6%. This outcome is expected since many areas within the county have a low rate of Airbnb listings.

Table 10
Overall price effects of Airbnb (in 2018).

		Baseline scenario			Counterfactual scenario 1: no HSOs			Counterfactual scenario 2: only HSOs		
	Average house price (in 1000 $)	*Listings rate (in %)*	*in % of the house price*	*Yearly effect (in $)*	*Listings rate (in %)*	*in % of the house price*	*Yearly effect (in $)*	*Listings rate (in %)*	*in % of the house price*	*Yearly effect (in $)*
Total predicted price effects of Airbnb listings:										
LA county	1053	1.21	3.62	1258	1.26	3.78	1313	0.91	2.73	949
Total predicted price effects near Hollywood:										
Hollywood <10km	1688	3.07	9.22	5136	3.10	9.29	5174	2.86	8.59	4786
Hollywood <5km	1960	4.89	14.66	9483	4.92	14.77	9549	4.54	13.63	8814
Hollywood <2.5km	2446	6.68	20.05	16,182	6.70	20.10	16,225	6.17	18.53	14,955
Total predicted price effects near the beach:										
Beach <10km	1099	1.58	4.75	1723	1.64	4.93	1788	1.38	4.14	1502
Beach <5km	1128	1.93	5.79	2154	2.03	6.09	2266	1.69	5.06	1884
Beach <2.5km	1113	2.44	7.32	2691	2.57	7.73	2839	2.13	6.38	2344
Total predicted price effects for specific neighborhoods:										
Venice	1212	12.77	38.33	15,327	12.77	38.33	15,327	8.92	26.78	10,709
West Hollywood	1593	3.55	10.65	5597	5.10	15.29	8038	3.55	10.65	5597
Malibu	2193	5.89	17.67	12,791	5.89	17.67	12,791	4.15	12.45	9009
Santa Monica	1645	1.76	5.29	2870	2.80	8.40	4564	1.76	5.29	2870
Redondo Beach	888	1.17	3.51	1029	1.49	4.46	1308	1.17	3.51	1029
Pasadena	928	0.96	2.88	882	1.29	3.87	1184	0.96	2.88	882

Figure 3 Regression analysis results of Airbnb's effects on different areas of Los Angeles.

However, there are specific regions where the listings rate is significantly higher. For instance, focusing on areas within 5km of Hollywood's Walk of Fame, a popular tourist destination, where the listings rate exceeds the county's average by more than four times, the estimated effect on house prices due to Airbnb is substantial at 14.7%. When narrowing our analysis to areas within 2.5km of the Walk of Fame, the effect becomes even more pronounced, reaching 20%. We also examine the effects of Airbnb in beach towns. Within 2.5km of the beach, the estimated price increase attributable to Airbnb is 4.8%. However, when considering specific cities and neighbourhoods, the impact of Airbnb on property prices varies significantly. In Venice, one of LA's most popular neighbourhoods, the total price increase exceeds 30%. Conversely, in Pasadena, located approximately 15km from Downtown LA, the effects of Airbnb are more modest. Let us now explore two counterfactual scenarios. Firstly, if all home-sharing organizations (HSOs) were abandoned, within 2.5km of a beach, this would lead to an approximate 5% increase in the listings rate and a 0.3% increase in house prices. In the case of

Santa Monica, known for its stringent HSO regulations, the listings rate would rise by 60% and house prices by nearly 2.5%, which is a noteworthy change. However, for areas in close proximity to Hollywood, where HSOs are rarely targeted, abandoning HSOs would not result in significant shifts in property values. Conversely, if all cities were to implement HSOs, it could have substantial effects in tourist-attractive areas. For example, in Venice, the listings rate would decrease by 30%, and house prices would decline by 11.6%. Hence, HSOs are likely to have a considerable impact in areas that draw in tourists. Our findings also indicate that in neighbourhoods appealing to tourists, the distributional consequences of Airbnb are significant. In popular areas, incumbent homeowners have benefited financially, gaining over $3,000 to $15,000 per year due to Airbnb. However, renters have likely experienced a corresponding loss as they are prohibited from listing their properties on Airbnb while facing higher rental costs simultaneously.

Furthermore, an analysis of Airbnb's influence on house prices and rents in Portugal was found in the literature (Franco & Santos, 2021). By utilizing data sourced from Airbnb, along with quarterly housing rents and prices from 106 municipalities in Portugal between 2012 and 2016, as well as additional relevant datasets for control variables, this study investigates the impact of Airbnb listings concentration, referred to as Airbnb share, on house prices and rents in Portugal. The analysis specifically focuses on the municipalities of Lisbon and Porto, which have witnessed significant increases in housing costs and the proliferation of Airbnb listings since 2014. The subsequent table presents the outcomes of ordinary least squares (OLS) and instrumental variable (IV) regressions, examining the effects of Airbnb share in a municipality on the logarithm of home sale prices and rental prices.

Table 4
OLS and IV estimates of the effect of Airbnb Share in a municipality on home sale prices and rents.

Method:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	FE	IV	IV	OLS	FE	IV	IV
Dep. Variable:	Ln(Home Sale Price)				Ln(Rent)			
Airbnb Share	7.612***	3.088**	3.738***	2.502*	2.907*	0.139	0.385	−0.246
	(1.780)	(1.314)	(1.370)	(1.432)	(1.613)	(0.828)	(0.856)	(0.907)
Observations	791	791	791	757	884	884	884	850
R^2-adjusted	0.805	0.878	–	–	0.846	0.908	–	–
IV first stage (Fstat and pval)			687 0.000	655 0.000			761 0.000	729 0.000
Endogeneity (pval)			0.325	0.910			0.543	0.875
Quarter-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Covariates	Yes	No	No	No	Yes	No	No	No

Notes: *Significance levels*: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Standard errors in parentheses clustered at the municipality level. Simple OLS results with municipality level covariates reported in columns (1) and (5). Columns (2) and (6) introduce fixed effects at the municipality level. The instrument in columns (3) and (7) is the interaction of google time trends for the word "Airbnb" times the share of properties on Airbnb in the first quarter of 2014 (before the policy). Finally, columns (4) and (8) exclude the municipalities of Lisbon and Porto.

Figure 4 Regression analysis results of Airbnb's effects on cities in Portugal

In the first column, the results indicate that a one percentage point (1pp) increase in Airbnb share corresponds to an average 7.61% increase in housing prices within the municipality. It should be noted that this specification incorporates time fixed-effects, but the controls are time-invariant and do not account for unobserved characteristics.

Moving to column 2, the introduction of municipality fixed effects reduces the estimated coefficient to 3.09. This suggests that, on average, a 1pp increase in Airbnb share results in a 3.09% increase in house prices. Meanwhile, column 3 presents IV results, incorporating both municipality-level and time fixed-effects. In this case, a 1pp increase in Airbnb share is associated with a 3.74% increase in home sale prices within the municipality. Column 4 replicates the IV analysis but excludes the municipalities of Lisbon and Porto. The exclusion of these cities slightly diminishes the previous estimate, although the results remain statistically significant. Specifically, a 1pp increase in Airbnb share is now linked to a 2.5% increase in house prices, on average, within the municipality.

Lastly, columns 5 to 8 reproduce the same specifications while employing the logarithm of rental prices as the dependent variable. Like the findings in the house price regressions, accounting for municipality amenities and characteristics is crucial, as the estimated impact of Airbnb share diminishes with the inclusion of controls. However, in contrast, the analysis does not reveal a statistically significant influence of Airbnb share on long-term rental prices. The researchers posit that this lack of significance could be attributed to the overlap of the phasing-out period of the 2012 rental market liberalization with the study period.

2.1.4 Social impact of Airbnb

The last strand to be analysed in this literature review concerns the impact Airbnb has from a social point of view. The impact of tourist accommodation in residential neighbourhoods has been a topic of debate among researchers and urban planners. On one hand, proponents argue that it brings economic benefits, enhances local businesses, and boosts tourism revenue, which can positively influence property values in the area. However, there is an opposing viewpoint that highlights potential negative consequences. According to this perspective, the presence of tourist accommodation, such as vacation rentals or short-term stays, can lead to an increase in criminal activities within the neighbourhood, subsequently impacting property values.

The reasoning behind this argument lies in the transient nature of tourists, which may create an environment susceptible to opportunistic crimes like theft, vandalism, or disturbances. Moreover, the continuous flow of new visitors unfamiliar with the neighbourhood's rules and norms could potentially disrupt the community's social fabric and lead to a perceived decrease in safety and security. A surge in criminal activities can generate fear and unease among residents, reducing the overall desirability of the area for potential homebuyers and long-term renters. As a result, the demand for properties may decrease, putting downward pressure on property values. Homeowners, worried about the potential risks associated with living in a tourist-heavy neighbourhood, might also be less inclined to invest in property maintenance and improvement, further impacting the overall aesthetics and appeal of the area.
The study 'The paradox of Airbnb, crime and house prices: A reconciliation' (Cheung, & You, 2022) aims to investigate the impact of Airbnb on the increase or decrease in crime and consequently the effect on house prices. Utilizing housing transaction data from two census years in the Auckland Region, New Zealand, our study examines the interplay between crime rates and Airbnb density on house prices. By accounting for various neighbourhood characteristics, such as household incomes, ethnicity concentration, and the proportion of public housing in each census tract, we find that the influence of crime on house prices is contingent on the prevalence of Airbnb listings. Notably, the negative impact of crime rates on house prices is mitigated by the number of Airbnb listings, particularly in the context of apartment-type housing. This outcome indicates the potential effects of trespassing-related crime on residential property values.
The concept of racial discrimination in the rental market is not new. Historical evidence and contemporary studies have highlighted instances of bias, where individuals from certain racial or ethnic groups may face unequal treatment when seeking housing. While anti-discrimination laws exist to protect against such practices in traditional housing markets, the sharing economy operates in a relatively less regulated space, potentially exposing it to a higher risk of discrimination.
In the case of Airbnb, concerns have been raised about whether hosts consider the race or ethnicity of potential guests when setting rental rates or deciding whether to accept booking requests. This type of bias can manifest itself in different ways, from outright refusal of certain guests based on their race to subtle price differentials depending on the guest's perceived background.
The study "The Visible Host: Does race guide Airbnb rental rates in San Francisco?" (Kakar, Voelz, Wu & Franco, 2017) aims at understanding if there is a relationship between the rental

rates and the race of hosts in the city of San Francisco. On average, the analysis reveals that Asian and Hispanic hosts set rental prices that are 8% to 10% lower compared to their White counterparts for similar rental properties. These findings are based on controlling for various factors, including renter-provided information on rental unit characteristics, neighbourhood property values, area demographics, and occupancy rates. Importantly, the researchers did not observe any differences in occupancy rates between minority and White hosts.
These results suggest a few possible explanations. One possibility is that minority hosts price their rentals lower due to forward-looking behaviour. They may anticipate potential discrimination in the online marketplace and adjust their prices accordingly to attract a larger pool of potential renters or maintain their target occupancy levels. Alternatively, it could be that minority hosts prefer increasing demand by offering lower prices, thus increasing their chances of securing bookings.

Through the literature study developed, it is possible to understand how far the analysis of Airbnb's effects on the economy of large cities has come. At the same time, it also suggests to us that there is a gap to be bridged regarding the effects on smaller towns. The aim of this thesis is precisely to try to bridge this gap by analysing the impact of Airbnb on Italian villages through the construction of econometric model.

Chapter 3: Research Methodology

3.1 Research study

After reviewing the existing literature, a noticeable research gap has surfaced regarding the impact of Airbnb on various regions. Specifically, prior studies have exclusively examined the effects of Airbnb's presence on major global cities' economies, neglecting its influence on villages. Precisely in order to try to fill this gap in the current literature, the following research study will analyse the effects that the digital platform creates on Italian villages and in particular aims to answer the following questions:

- What impact does Airbnb's entry have on the online visibility of a village?

- Does Airbnb improve the economic condition of rural and emerging areas?

- How are local job opportunities in a village complemented by digital platforms such as Airbnb?

Hypothesis 1

"The entrance of Airbnb leads to an increase in the online visibility of villages. "

By studying the online visibility of villages before and after Airbnb's introduction, this research could reveal its influence on local economies, tourism development, cultural exchange, and community perceptions. Additionally, it may highlight the potential for sustainable tourism and shed light on any digital divide between villages with and without Airbnb. Ultimately, this investigation could offer valuable insights to guide policymakers in fostering responsible and balanced growth while preserving the unique identities of rural communities.

Hypothesis 2

"The entrance of Airbnb stimulates the economy growth of villages. "

Airbnb's presence in rural areas might stimulate economic growth through increased tourism and spending. Understanding the specific economic impacts, such as job creation, income generation, and business growth, can provide valuable insights for policymakers, entrepreneurs, and local communities. It could also help assess whether short-term rental platforms like Airbnb can play a positive role in fostering economic opportunities in rural regions, which may have previously struggled to attract visitors and investment.

Hypothesis 3

"The entrance of Airbnb creates new job opportunities, and it leads to an increase in active population. "

The growth of Airbnb and its associated tourism activities creates job opportunities for locals, particularly in service-related sectors like hospitality, cleaning, and tourism services. This could be especially relevant for rural areas where employment opportunities might be limited. On the other hand, if the hypothesis is not supported, it could raise questions about the sustainability and inclusivity of Airbnb's economic impact. Understanding the relationship between Airbnb's entrance and the local active population (the amount of people who are actively search for an employment or are already working) can offer valuable insights into the platform's role in the labour market dynamics of different regions and guide policies aimed at maximizing the positive outcomes on employment.

For all three hypotheses, an attempt was also made to understand whether the impact of Airbnb's entry on each of these three areas differs, according to certain characteristics of the village. The first characteristic that we decided to evaluate concerns the accessibility of the village, that is, the ease of reaching it by means of transport. This element, in fact, could influence the impact of Airbnb's entry on the borough; the objective of this more detailed analysis is precisely to try to understand how Airbnb's impact varies for each of the three hypotheses made. A similar discourse is made for the second characteristic we decided to investigate, namely tourism of a cultural nature as measured by the presence or absence of museums in the village.

3.2 Data Collection

The dataset comprises 269 Italian villages spanning across all geographical regions of Italy, encompassing both islands and Northern areas. The range of years included in this dataset is from 2009 to 2019. The information utilized for the analysis was sourced from various platforms, including:

- Airbnb data, obtained from the AIRDNA website.
- Economic indicators, extracted from the Ministry of Economy and Finance's official website.
- Other village-related variables, gathered from the official ISTAT website.

Specifically, the dataset encompasses various categories of information, including:

- General details for villages identification: this initial set of data comprises the observation year (YEAR), geographical area (NUTS1), region (NUTS2), province (NUTS3), ISTAT code (ISTATcode), ISTAT-registered name of the village (BORGO-ISTATname), year and name of the village (BORGO-YEAR).
- Variables pertaining to Airbnb and the count of existing Airbnb establishments in the villages.

- Information about village population and its changes over time.
- Data related to accommodation pricing within the villages.
- Income-related variables.
- Variables linked to Google trends.
- Variables associated with the hospitality sector within each village.
- Structural attributes of the village, including facility presence and distance from the airport.
- Economic indicators like GDP, HCPI and unemployment rate.

3.3 Research Methodology

The aim of this study is to investigate what influence Airbnb's entry has on the society of Italian villages. It starts with an overall trend analysis, then goes on to analyse the variables of greatest interest and on which we will focus in this research. A regression analysis will then be carried out to confirm the results obtained in the descriptive analysis.

The first step to gain a complete understanding of the data at one's disposal is to carry out an exploratory data analysis known as Exploratory Data Analysis. This allows you to get an idea of how the data is organised, to understand the most interesting variables in your research and to get information on the relationships between the different data.
The first part of the analysis will be carried out using descriptive statistics. Descriptive statistics is a branch of statistics that focuses on the collection, synthesis and interpretation of data to describe and summarize the main characteristics of a data set or distribution. This type of statistics provides methods and tools for organising data in an understandable way using graphs, tables, measures of central tendency (such as mean and median), measures of dispersion (such as variance and standard deviation) and other summary statistics. The main objective of descriptive statistics is to make data more accessible and understandable, allowing analysts to draw preliminary conclusions about the data and to effectively communicate the information gathered.

After conducting an initial exploratory analysis of the data and finding the descriptive statistics, we proceed with a regression analysis. Regression analysis is a statistical technique used to study and quantify the relationship between a dependent variable (or response variable) and one or more independent variables (or predictor variables). The main objective of regression analysis is to understand how variations in the independent variables influence the dependent variable. This is done by creating a mathematical or statistical model that attempts to describe this relationship. The regression model can be linear or non-linear, depending on the nature of the data and the assumption about the relationship between the variables. It can also be simple or multiple, depending on whether there is a single or multiple independent variables. Once the model is established, it can be used to make predictions or to better understand how the independent variables influence the dependent variable. The most common method used in regression analysis is called Ordinary Least Squares (OLS), which is a method of estimating the parameters of the regression model. OLS tries to find the line (or surface, if it is a multiple regression model) that minimises the sum of the squares of the differences between the observed values of the dependent variable and the values predicted by the model. In other words, it tries to find the coefficients that minimise the discrepancy between the actual data and the model's predictions.

3.4 Tool Used in the Analysis

EXCEL

Excel is a powerful spreadsheet program developed by Microsoft. It allows users to store, organize, manipulate, and analyse data in a tabular format, making it an essential tool for data analysis. Excel's importance in data analysis lies in its ability to handle and process large amounts of data efficiently and accurately. It offers a wide range of functions, formulas, and statistical tools that aid in performing various data analysis tasks, such as summarizing numerical data, finding trends, comparing data sets and generating reports. One advantage in using Excel for descriptive statistics analysis is its ease of use. Excel provides a user-friendly interface with a familiar spreadsheet layout, making it accessible for users of all levels of expertise. Its intuitive features allow users to enter and organize data quickly, and the built-in formulas and functions simplify calculations in descriptive statistics. This makes it an ideal tool for beginners in data analysis as well as advanced users who require complex statistical analysis. Additionally, Excel offers a wide range of statistical functions that can be utilized for descriptive statistics analysis. These include measures such as mean, median, mode, range, standard deviation, variance, skewness, kurtosis, and quartiles. Excel also provides various charts and graphs, such as histograms, scatter plots, and line plots, which enable users to visually represent and interpret data, aiding in better understanding and analysis. Another advantage of using Excel for descriptive statistics analysis is its versatility. Excel allows users to import data from various sources, such as databases, text files, or external applications, facilitating seamless integration with different data sets. It also provides powerful data manipulation capabilities, enabling users to sort, filter, and transform data to meet specific analysis requirements. Moreover, with Excel's pivot table functionality, users can summarize and aggregate large datasets with ease, allowing for more efficient data analysis. Excel's widespread popularity and availability make it an advantageous choice for descriptive statistics analysis. It is widely used in various industries, such as finance, marketing, research, and academia, due to its compatibility with other Microsoft Office applications and its ability to generate detailed reports. Furthermore, Excel supports the use of macros and Visual Basic for Applications (VBA), allowing users to automate repetitive tasks and customize data analysis workflows, improving efficiency and productivity. In conclusion, Excel is a crucial tool for data analysis, enabling users to efficiently organize, manipulate, and analyze large datasets. Its user-friendly interface, extensive statistical functions, versatility, and automation capabilities make it an advantageous choice for descriptive statistics analysis. Whether for simple data summaries or complex statistical modeling, Excel provides the necessary tools to extract valuable insights from data, making it an indispensable tool in the field of data analysis.

STATA

STATA is a widely acclaimed software package utilized in both academic and professional spheres that offers a robust suite of functions, including an exceptional capability to conduct regression analysis. Developed by StataCorp, this versatile tool serves as an invaluable asset for researchers seeking to explore intricate data relationships and derive meaningful insights. What sets STATA apart is its ability in running various forms of regression analysis, from linear and logistic regression to more advanced models like panel data, multilevel, and time series regression. These analytical techniques enable researchers to uncover hidden patterns, establish causal relationships, and make predictions based on complex datasets. STATA's user-friendly interface empowers researchers of diverse skill levels to seamlessly execute regression analysis.

Researchers can either employ a command-line approach, utilizing STATA's intuitive programming language, or take advantage of graphical user interfaces (GUIs) for a more visual and interactive experience. This flexibility accommodates both coding-savvy individuals and those who prefer point-and-click interactions, streamlining the process of specifying, running, and interpreting regression models. Moreover, STATA facilitates the handling of various data types and formats, allowing researchers to effortlessly prepare their data for regression analysis. This includes tasks like data cleaning, manipulation, and transformation, ensuring the reliability and accuracy of results. The software's extensive suite of built-in regression diagnostics and post-estimation tools empowers researchers to assess the validity of their models, identify outliers, check for multicollinearity, and evaluate the overall goodness of fit. In conclusion, STATA's exceptional functionality to run regression analysis positions it as a fundament in data-driven research. Its versatility, ease of use, and robust array of regression techniques make it an indispensable tool for researchers seeking to uncover meaningful insights and draw accurate conclusions from their data. Whether delving into basic linear relationships or exploring intricate interactions, STATA provides the tools needed to navigate the complexities of regression analysis and extract valuable knowledge from diverse datasets.

Chapter 4: Preliminary Analysis

4.1 Descriptive Analysis

The first step for a proper data analysis is the investigation of the database at hand. As explained in the previous chapter, this will be done through a descriptive analysis that aims to provide a clearer view of the trends we wish to explore in this study. In particular, the analysis of the dataset will be carried out through descriptive statistics, one for each of the three hypotheses presented above.

First, the dataset was transported into Excel, which allows for easier and faster manipulation and cleaning of the data due to the user friendliness of the software.

The statistical procedure that will be used in the descriptive study is the Difference-in-Differences method. Difference-in-Differences (DID) analysis is a statistical technique used in economics, social sciences and other fields to assess the causal effect of a treatment, intervention or change on a group of observations. Specifically, DID analysis compares changes over time between a treatment group (exposed to the intervention) and a control group (not exposed to the intervention) to determine whether the treatment had a significant impact. The DID approach exploits pre-existing differences between the treatment and control groups before

the intervention and attempts to control for these differences when analysing the treatment effect. The fundamental logic of the DID analysis is based on comparing the variations 'before and after' the intervention within the treatment and control groups and then comparing the differences in these variations between the two groups.
Since this approach compares changes over time between treatment and control groups, it is essential to obtain valid panel data results, that are multiple observations for the same units over time. Panel data make it possible to control for unobserved variables, manage confounders and identify causal effects. This is because they make it possible to compare pre and post intervention dynamics within each group.

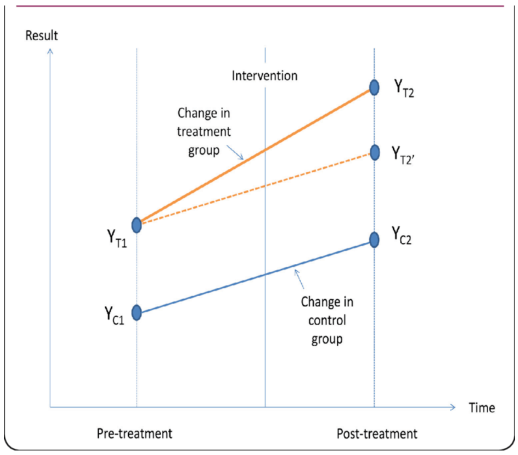

Figure 5 Difference-in-Differences Analysis

As we can see in the picture above, both data of a specific dependent variable in the control group and those of the treated group are first measured at a specific time. In this way, two pre-treatment time values (Y_{c1} and Y_{t1}) are obtained for both groups. Subsequently, values are measured again for the same variable at a later time, defined as post-treatment (Y_{c2} and Y_{t2}). At this time interval, the dependent variable undergoes the treatment. As can be observed in the figure, the value of the treated group is altered; in fact the slope of the line passing through points Y_{t1} and Y_{t2} has a different slope to the line passing through points Y_{c1} Y_{c2}. In fact, the slope of the latter line is the same as that of the dotted line in the figure, i.e. the line passing through the points Y_{t1} and $Y_{t2'}$. In fact, the point $Y_{t2'}$ represents the value of the dependent variable if it had not undergone the treatment. The effect of the treatment is represented by the difference on the y-axis of the points Y_{t2} and $Y_{t2'}$.

A fundamental prerequisite in DID (Differences-in-Differences) analysis is the "parallel trend" hypothesis and refers to the condition that the baseline (pre-intervention) trends in the treatment and control groups are similar or parallel prior to the introduction of the intervention. This is an essential prerequisite for DID analysis because it allows the effect of the intervention itself to be properly controlled. In other words, the parallel trend hypothesis implies that, had there been no intervention, the differences in outcome between the treatment and control groups would have remained constant over time, based on pre-existing trends.

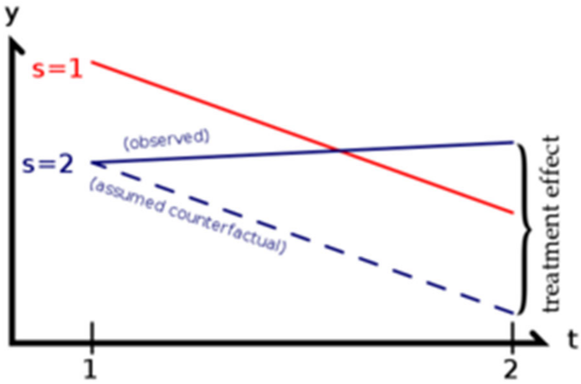

Figure 6 Parallel Trend Assumption

An important analytical measure often used in the descriptive statistics is called ATE (Average Treatment Effect) and it is used to quantify the average effect of a treatment or intervention on a group of observations. The ATE represents the average difference between the outcome of a treated group (exposed to the intervention) and the outcome of a control group (not exposed to the intervention). The ATE (Average Treatment Effect) and the "parallel trend hypothesis" are related concepts in the context of DID (Differences-in-Differences) analysis and they are both important for drawing reliable conclusions about the causal effects of a treatment or intervention. The parallel trend hypothesis is crucial in order to correctly interpret ATE. If the underlying trends are not parallel, the ATE could be influenced by pre-existing differences that have not been controlled for.

Before going into the details of the three descriptive statistics analysed, since the dataset at our disposal is a panel type dataset, a dataset comprising multiple observations for the same units of analysis over time, we need to identify the two different moments that will be taken into consideration. First of all, it was identified how many villages per year the Airbnb platform entered. As can be seen from the table in the years from 2010 to 2014 the highest number of entries occurred, with a higher concentration in the middle 3 years. While there is a fairly high number, representing slightly more than 25% of our dataset, of villages in which Airbnb did not enter in the entire period considered. The first moment chosen is the year 2013, which falls within the previously mentioned time period, while the second moment is the last time reference we have in our dataset, which is 2019. In all three descriptive statistics that will be presented later, the treated group considered are the villages that have seen the entry of Airbnb in the time period 2009-2019, while in the control group we have the villages in which Airbnb is not yet until 2019.

Year	Number of villages where Airbnb entered per year	Number of villages where Airbnb never entered in the period considered
2009	2	
2010	19	
2011	48	
2012	55	
2013	48	
2014	20	71
2015	6	
2016	0	
2017	0	
2018	0	
2019	0	

Figure 7 Airbnb Entrance per Villages

4.1.1 First Descriptive Statistics: Effect of Airbnb's Entrance on Villages' Online Visibility

The first description aims to analyse the impact of Airbnb's entry into villages on the online visibility of the villages themselves. The variable in our dataset that was used to estimate the online exposure of the specific village is called "AVG_GoogleTrendsIndex" which represents an arithmetic mean between the variables "MAX_GoogleTrendsIndex" and "MIN_GoogleTrendsIndex". These two variables represent the maximum value and the minimum value of the normalised popularity index recorded for searches related to that village on Google Trends. This popularity index is clearly analysed within an annual time interval and can vary from 0 (minimum value) to 100 (maximum value).

As highlighted in the previous paragraph, the 2013 cohort was analysed using the Difference-in-Differences methodology. Using Excel's SUMIFS function, it was possible to calculate the PRE Treatment Averages (2013) and POST Treatment Averages (2019) of both the control and treated groups. Below are the tables:

	Pre Treatment Average (2013)
Control Group	28,13
Treated Group	28,73

	Post Treatment Average (2019)
Control Group	35,96
Treated Group	37,27

Figure 8 Pre & Post Averages Descriptive 1

After collecting this data, it is necessary to apply Difference-in-Differences. This helps to have a clearer comparison between the two groups analysed. In fact, if only one has been analysed, looking at the data in the tables above, one could guess that the average online visibility of the villages in the two groups increased; but there is no clear distinction whether there was a greater benefit in one of the two populations or not. Therefore, the percentage change the two groups had over the period analysed was calculated; and here are the results:

	Percentage Change	ATE
Control Group	27,8%	1,9%
Treated Group	29,7%	

Figure 9 Percentage Variation & ATE Descriptive 1

As can be seen from the table above, the percentage increase of the treated is greater than that of the control group; in fact there is a 1.9% difference reflected in the ATE. This is also highlighted by the following graph where the slope is greater in the treated group than in the control group since the orange line which approximates the trend of the average online visibility of the treated group is more sloping than the grey dotted line which approximates the trend of the average online visibility of the villages in the treated group if the latter had not undergone it.

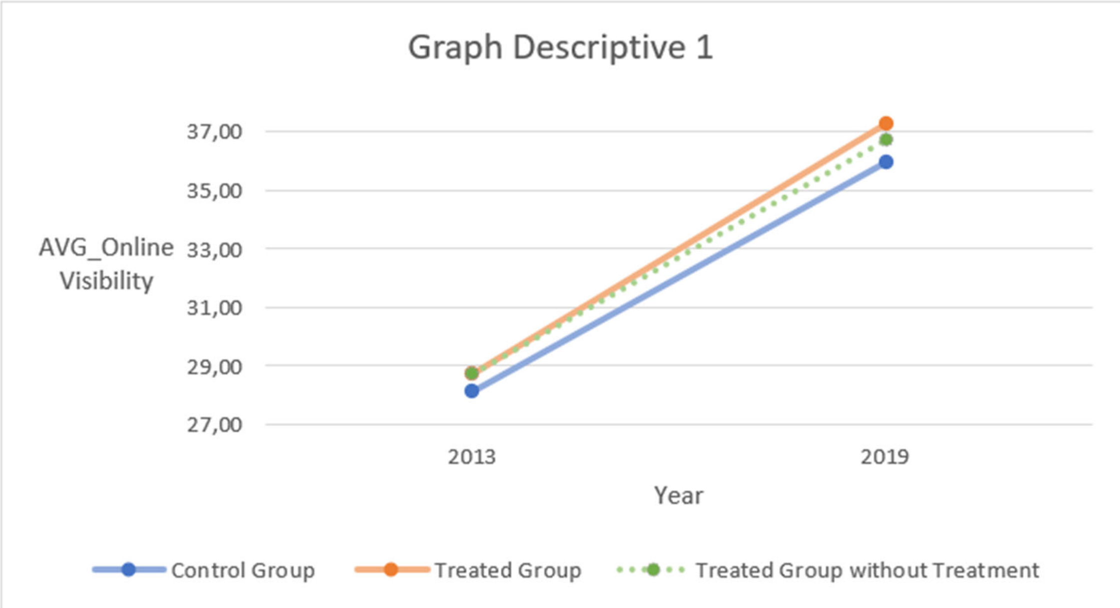

Figure 10 Trend Descriptive 1

4.1.2 Second Descriptive Statistics: Effect of Airbnb's Entrance on Villages' Economy

The second descriptive statistic aims to analyse whether there is a relationship between the entry of Airbnb and the economic growth of the village. The control group and the treated group are still the same as in the previous descriptive statistic. In this case, the variable analysed in our dataset clearly changes, as a matter of fact it is no longer linked to the online visibility of the village but is a variable that estimates the economic value produced by a given village over a specific period. The variable in question in our dataset is the village's Ordinary Entrepreneur Income per capital. It is an economic variable that represents the average income earned by individuals or businesses engaged in typical entrepreneurial activities within a specific population. It is a measure that helps to assess the economic performance of a group in terms of income generated by entrepreneurial activities on an individual basis. It is also a useful indicator for analysing the economic well-being of different regions or for tracking changes in entrepreneurial income over time. As one can guess from its description, it is a measure often considered a 'positive variable' or a 'positive indicator', meaning that a higher value is considered desirable.

Again, the DID methodology was used for the 2013 cohort. To maintain consistency between the three descriptive statistics, the time instants analysed remain 2013 and 2019. Using Excel's SUMIFS function, the average Entrepreneur Income per capital value of the villages in the control group and that of the villages in the treated group were calculated.

The control group has 71 villages while the treated group counts 198 villages, as well as the previous case. Given these premises, the average Ordinary Entrepreneur Income per capital pre-treatment and post-treatment values are presented below:

	Pre Treatment Average (2013)
Control Group	9002,18
Treated Group	14536,25

	Post Treatment Average (2019)
Control Group	10787,17
Treated Group	20347,76

Figure 11 Pre & Post Averages Descriptive 2

As can be seen from the tables above, in both the control and the treated group, there is an increase in the average of entrepreneur income per capital over the years. This is due to a probable economic growth of the small Italian villages included in our analysis. Then, to understand whether there is a link with the entry of Airbnb or not, it is necessary to continue with the Difference-in-Differences analysis and calculate the percentage changes and consequently the ATE.

	Percentage Change	ATE
Control Group	18,2%	21,8%
Treated Group	40,0%	

Figure 12 Percentage Variation & ATE Descriptive 2

Regarding entrepreneur income per capital, as shown in the table above, there is a substantial increase over the period 2013-2019 for both populations analysed. This may be dictated by

several factors such as economic growth, increased production of goods and services, investments, innovation and development of growth sectors. The ATE is 21,8%; this means that there is a considerable increase in the treated group compared to the control one.
Below is also reported a graph of the straight line that approximates the two measured values. As can be seen from the figure, there is a slight slope of the orange line that approximates the trend of the average entrepreneur income per capital of the treated group compared to the dotted line, which again approximates the trend that the treated group would have had without the treatment, the entry of Airbnb.

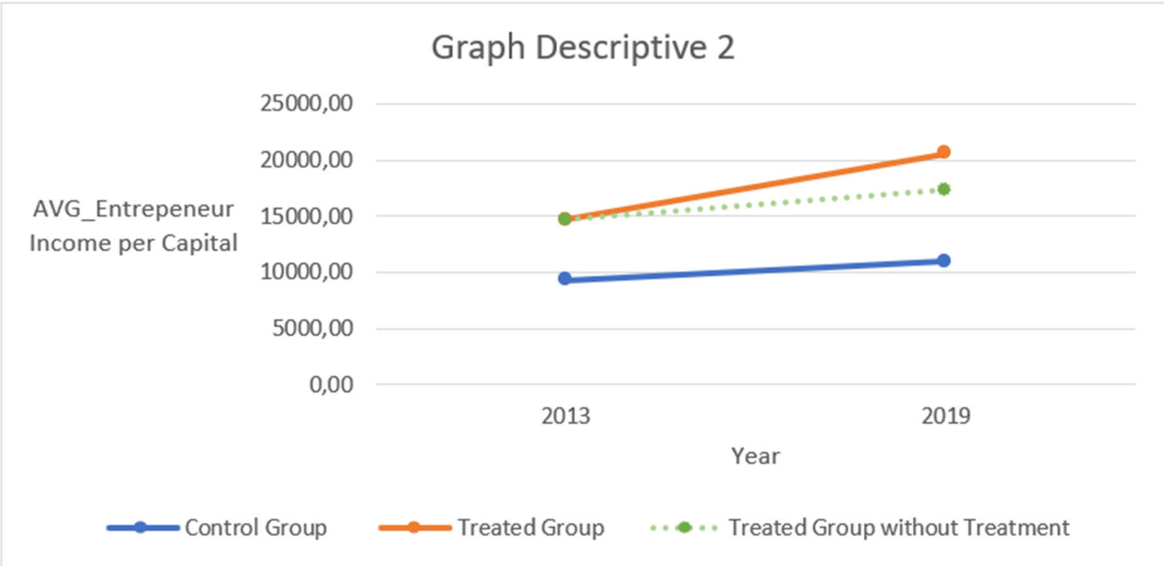

Figure 13 Trend Descriptive 2

4.1.3 Third Descriptive Statistics: Effect of Airbnb's Entrance on Villages' Active population

The third and last descriptive statistic that will be analysed in this chapter aims to investigate whether the entry of Airbnb in Italian villages has had an influence on the possibility of employment in these communities. As in the previous two descriptive statistics presented, we have, as control group, the Italian villages in which Airbnb did not enter until 2019 and, as treated group, the villages in which Airbnb entered before 2019.

In this analysis, as mentioned, we will evaluate how Airbnb influences the possibility of employment of the population. To measure it, the variable 'active population' was used. The active population is defined as the part of the population of a state or city that is able, except for temporary impediments, to legally work. It was decided to use this variable because the unemployment rate is defined at the provincial level, whereas the active population is specific to each village and thus allows us a more precise and detailed analysis. As the two indicators previously used, this type of indicator is referred to as a positive indicator, since a higher value of the indicator is preferable. To maintain consistency between the three descriptive statistics presented, the study again considers the 2013 cohort by analysing it using the DID methodology. As well as the previous two cases, for the measurement of this descriptive statistic, the control group has 71 villages while the treated one has 198. The procedure used in this situation was the same as well, starting by calculating the average value of the active population for the two groups at the predefined time instants (2013 and 2019), using Excel's SUMIFS function. The results are summarised in the tables below:

	Pre Treatment Average (2013)
Control Group	2124,46
Treated Group	4089,02

	Post Treatment Average (2019)
Control Group	1866,42
Treated Group	4138,01

Figure 14 Pre & Post Averages Descriptive 3

As suggested above and as can be seen from the results in the previous tables, the average active population has decreased in the villages of the control group whereas it increased in the treated one. This suggests that the entry of Airbnb is beneficial, increasing the possibility of employment for villages' population. To confirm this first assumption, DID and ATE were calculated.

	Percentage Change	ATE
Control Group	-10,9%	13,1%
Treated Group	2,2%	

Figure 15 Percentage Variation & ATE Descriptive 3

As explained by the data above, there is a percentage decrease in the active population of more than 10% for the control group whereas there is a slight increase for the treated one. In this case the ATE is 13.1%; so the data suggests that there is a greater increase in the active population in the villages that saw the entry of Airbnb by 2019 than in the villages where Airbnb did not enter. In conclusion, as for the other two statistics, I report the graph showing the slope of the lines approximating the two values measured by the two groups at the given time instants. As can be seen from the graph, the orange line, which again represents the active population trend over the period studied, has a steeper slope than if the group had not undergone the treatment represented by the green dotted line. This means that the entry of Airbnb has resulted in a percentual increase of the active population.

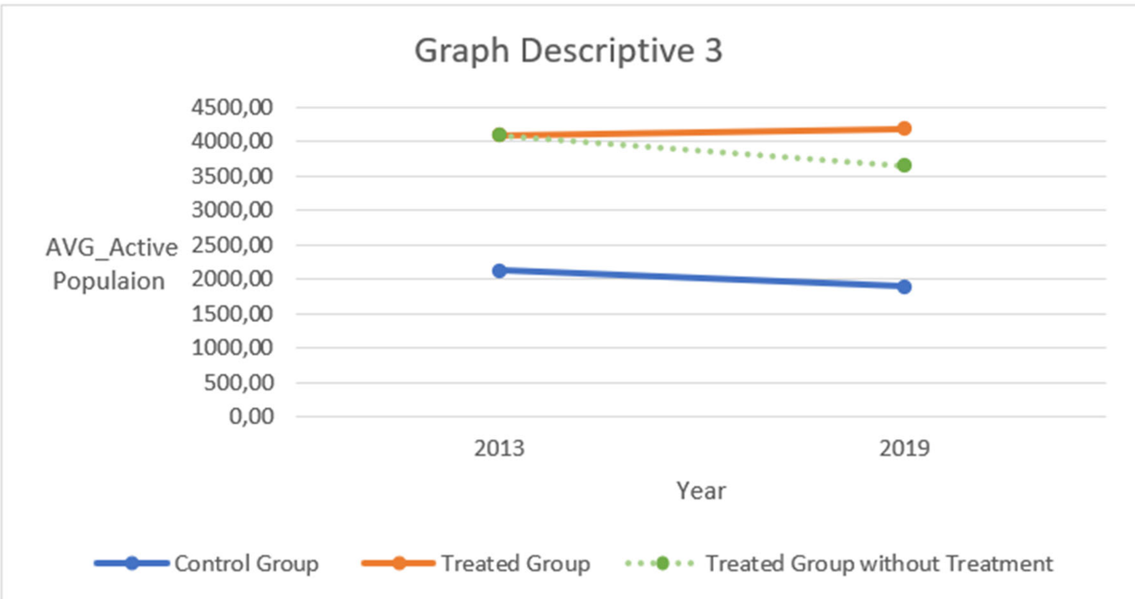

Figure 16 Trend Descriptive 3

4.2 Results Descriptive Analysis

To allow a clearer understanding of the results, it was deemed appropriate to summarise the results of the descriptive analysis carried out in the previous paragraph. As presented above, to run the analysis the DID methodology was used and ATE was calculated to see and to assess the influence of Airbnb.

Below are the findings obtained:

- **Airbnb’s entry in Villages & Online Visibility:** in the first descriptive analysis, it was observed that in both groups there was a substantial increase, around 30%, in the online visibility of the villages. Regarding the villages that saw the entry of Airbnb, it can be seen that the increase was greater by about 2%.

- **Airbnb’s entry in Villages & Entrepreneur Income per capital:** in the second descriptive analysis carried out, which analysed the relationship between the Entrepreneur Income per capital of the villages and the entry of Airbnb, again in both groups an increase was seen in 2019 compared to 2013. For the villages that had Airbnb's entry into their territory this increase was much more pronounced, about 20% more.

- **Airbnb’s entry in Villages & Active Population:** in the third and last descriptive analysis carried out, the aim was to analyse whether there was a relationship between the entry of Airbnb in the villages and the active population of the villages themselves; it was noted that in the second period in which the data were measured (2019), there was a decrease of about 10% in the control group whereas there was a slight increase in the treated one; therefore, the calculated ATE is 13.1%, meaning that Airbnb increased the people with possibility to work in these villages.

In overall terms, from the analysis carried out it could be said that the entry of Airbnb had positive effects on the villages because in all the three cases it increased the online visibility of the villages, it increased the entrepreneur income per capital and there was a rise in the active population. In the next chapter, to confirm the validity of the results obtained through the descriptive analysis, regression analysis will be carried out.

Chapter 5: In-depth Analysis

5.1 Regression Analysis

Before going into detail about the regression analysis that were carried out in this study, it is important to define what underlies these types of analysis, namely econometrics. But what is meant by econometrics? One of the most widely accepted definitions is: *"Econometrics is the science of using mathematical and statistical tools to estimate economic relationships."* Accordingly, through this scientific discipline, the use of data allows to test previously formulated hypothesis and to understand the behaviour of certain variables.
Precisely, the primary objective of this science is to estimate whether there are casual relationships between variables. In the cases of this study, relationships between purely economic variables will be investigated, such as how the number of villages in which Airbnb has entered is impacting the online visibility, economy and unemployment rate of the communities themselves.

Econometric analysis of causal effects is conducted using non-experimental, observational data, which are gathered by observing real-world behaviour outside of an experimental setting. In econometrics, the data under consideration can be categorized into three types:

- **Cross-sectional data**: Information from multiple individuals measured only at a single specific point in time, that is the same for all the population.
- **Time series data:** Data obtained from a single individual observed over multiple time periods.
- **Panel data:** Information from multiple individuals observed over multiple time periods.

As outlined in the previous paragraph, the dataset used in this study is a panel data. In fact, regarding all the variables there are observations measured each year from 2009 to 2019 for all the several villages analysed.

The purpose of measuring random relationships between variables is realised by means of a mathematical model using the following equation:

$$Yi = \beta 0 + \beta 1X1 + \beta 2X2 + \ldots + \beta nXn + \varepsilon$$

where:

- ***Y_i*** = the observed value of the dependent variable at point i
- ***β_0*** = the y-intercept (constant value)
- ***β_n*** = the regression coefficient or slope for the explanatory variable N at point 1
- ***X_n*** = the value of variable N at point 1
- ***ε*** = the error of the regression equation

The most used methodology for estimating model parameters, i.e., betas, is the OLS technique, also known as method of least squares. The OLS estimator minimises the sum of the squares of the differences between the observed values of Yi and the values predicted from the estimated regression line.

Once the model parameters have been estimated, it is necessary to understand to what extent the model fits the data. To do this, normally two measures of goodness of fit are mainly assessed:

1) **Residual Standard Error, RSE.** It measures the average distance between the estimated and observed values. The smaller this value, the better the model's approximation to the data.
2) **Coefficient of determination, R2**. This measures the share of variability of Y that is explained by the model. The closer the value of R2 is to 1, the better the model's fit to the data, meaning that the estimated line passes close to the observed data. Values close to 0 indicate a poor fit to the data, which could be due to a high value of $\sigma 2$, the use of an unsuitable model (e.g., due to the assumption of linearity), or perhaps both of them impact on the poor result.

After having established the goodness-of-fit of a regression model, the last and most important step is missing in which one tries to determine whether the dependent variable Y is influenced by the independent variable (in the case of simple linear regression) or by one or more independent variables (in the case of multiple linear regression). In fact, one is interested in testing the null hypothesis H0: βj = 0, against the alternative hypothesis, H1: βj 6 = 0. The null hypothesis is equivalent to saying that the independent variable Xi does not influence the dependent variable Y. First, a level of significance must be set at which one wants to understand whether there is a relationship between these considered variables. Once this value has been defined, the p-value obtained is observed. This value indicates the significance level of the sample. If this number is lower than the decided significance level, the null hypothesis is rejected. Consequently, it is stated that there is an influence between the two variables, i.e., that the independent variable has an impact on the dependent variable.

5.2 Regression Analysis Results

In this section we will summarise the results of the regression analysis carried out to assess the correctness of the hypotheses made in chapter three. As can be seen in the previous chapter, already through the descriptives one has an idea of the validity or otherwise of the study's hypotheses, in fact it was noted that in the group of treated villages (i.e., those that suffered the entry of Airbnb) there is, on average, a growth in online visibility, a growth in GDP and a decrease in the unemployment rate. To confirm the assertions obtained from the descriptive analysis, regression analysis were run.

The first step was to create a dummy variable, i.e., a binary variable that was not present in our dataset, which would have a value of 0 if Airbnb had not entered that specific borough and a value of 1 if Airbnb had entered the borough in the time period analysed. To do this we used the variable called *"AIRBNBentry_year"* in our dataset which had a value of 0 if Airbnb had not entered that specific borough or the year of entry.

To do this we used the following STATA code:

"*gen Dummy = (AIRBNBentry_year != 0)* ".

The creation of this variable is crucial to the success of the analysis as it will be our main independent variable for all our hypotheses tests.

Regarding the first hypothesis, the dependent variable used is "AVG_GoogleTrendsIndex", which measures the average online visibility obtained by the village in a specific year. Having decided on our x (independent variable) and our y (dependent variable) we can run the regression.

The following code is used on STATA:

" *regress AVG_GoogleTrendsIndex Dummy i.YEAR, robust*" .

As you can see, *"regress"* is used to tell the software to run a regression analysis, then the dependent variable is entered, followed by the main independent. In turn, the entry *"i.YEAR"* tells STATA to generate the dummy for the entered variable (in this case the variable is YEAR) and finally "*robust"* is entered so that Stata calculates the standard errors robust to heteroskedasticity, that is, the property of random variables to have within them subpopulations that have different variances.

It is important to mention that we will use the same format for all the three simple and the three multiple regressions. In this case, since the independent variable is only one, it is a simple linear regression.

Below are the results obtained.

AVG_GoogleTrendsIndex	(1)
Dummy	3.564***
	(5.03)
_cons	32.675***
	(26.65)
Year FE	Yes
* p <0.05 ** p<0.01 *** p < 0.001	

Figure 11 First Hypothesis simple regression

As can be seen from the output of the analysis, the entry of Airbnb has a positive influence on the average online visibility of the villages, in fact the coefficient of the dummy is positive. The p-value referring to the independent variable, since it is below 0.05 at a 95% confidence interval, also allows us to affirm the significance of the model.

This is what happens in the case of a simple linear regression. To take into account the effects of other variables that might influence the dependent variable and to check how they influence the main independent variable, it was decided to test the hypothesis with a new model, this time of multiple linear regression. For simplicity, we will add two control variables, which we will keep in all three cases. The variables added are:

- *lnTotHospBeds:* it measures the natural logarithm of TotHospitalityBeds representing the number of beds, understood as availability, in the village in a specific year.
- *HCPI:* it is an economic variable that measures consumer price inflation.

Consequently, the runned regression was as follows:

"regress AVG_GoogleTrendsIndex Dummy HCPI lnTotHospBeds i.YEAR, robust"

AVG_GoogleTrendsIndex	(2)
Dummy	1.883* (2.43)
HCPI	-1.698*** (-5.62)
LnTotHospBeds	.863*** (4.07)
_cons	244.948*** (6.39)
Year FE	Yes
* p <0.05 ** p<0.01 *** p < 0.001	

Figure 12 First Hypothesis Multiple Regression

In this case as well can be seen that the 'Dummy' variable representing whether or not Airbnb enters the village is positively correlated with the average online visibility. The variable indicating the number of availabilities of the villages is also positively correlated, while a decrease in the village's inflation rate is linked to an increase in the same village's online visibility. Moreover, the p-value of the independent variable and the two control variables are close to zero, confirming that the analysis is significant at the 95% confidence interval.

Then, the second hypothesis that was tested, is that Airbnb's entry into a village have a positive influence on the village's Ordinary Entrepreneur Income per capital. As dependent variable Y, the natural logarithm of the variable measured within our dataset was used. We preferred to use the logarithm of the variable mainly for two reasons, as this eliminated the effect of the units of the variables on the coefficient and narrowed the range of the variable by a smaller amount than the original allowing for more accurate results.

The following code on STATA was used to transform the variable:

" gen lnRedditoImprenditoreOrdCAPITE = ln(RedditoImprenditoreOrdCAPITE)".

Subsequently, a simple linear regression was first run for the second hypothesis, with the dependent variable the natural logarithm of the Entrepreneur Income variable and the dummy variable estimating whether or not Airbnb had entered the village as independent.

The following input was used on STATA, with the following results:

"regress lnRedditoImprenditoreOrdCAPITE Dummy i.YEAR, robust".

LnRedditoImprenditoreOrdCAPITE	(1)
Dummy	0.103*** (3.99)
_cons	9.912*** (275.28)
Year FE	Yes
* p <0.05 ** p<0.01 *** p < 0.001	

Figure 13 Second Hypothesis Simple Regression

The regression results suggest that the entrance of Airbnb into a village has a positive correlation with the village's Entrepreneur Income per capital. Moreover, the result is also significant at a 95% confidence interval since the p-value of the independent variable falls below the 5% threshold.

Below we continue our analysis with multiple regression. Furthermore, in this situation we decided to analyse how, in addition to the binary variable used previously, the economic variable HCPI and the logarithm of the natural variable measuring the availability of beds in the village impacted, and the entry or non-entry of Airbnb remained significant.

The following STATA code was used, and the results presented below were obtained:

"regress lnRedditoImprenditoreOrdCAPITE Dummy HCPI lnTotHospBeds i.YEAR, robust"

LnRedditoImprenditoreOrdCAPITE	(2)
Dummy	.023 (0.80)
HCPI	-.022*** (-2.17)
LnTotHospBeds	.035*** (4.38)
_cons	12.567*** (9.79)
Year FE	Yes
* p <0.05 ** p<0.01 *** p < 0.001	

Figure 14 Second Hypothesis Multiple Regression

The regression analysis performed confirms the positive impact of Airbnb on the Entrepreneur Income per capital of the borough. Instead, there is a negative relationship between the dependent variable and HCPI. In fact, here an increase in the rate of inflation leads to a decrease in income per capital of the entrepreneur. The effect of the variable measuring bed availability on Entrepreneur Income is positive; in fact, the positive coefficient in this situation suggests a positive relationship between the variables and an increase in bed availability leads to an increase in the dependent variable.

The p-value of the two control variables being close to zero, suggests that the analysis is significant at the 95% confidence interval. As far as the main independent variable is concerned, as can be seen from the regression output in this case we have a fairly high p-value, so with the proposed model at a 95% confidence interval there is no statistical evidence for rejecting the null hypothesis.

The third and final hypothesis that was tested aimed to investigate what the relationship was between Airbnb entry and the active population of a village, that is those who are already employed or actively seeking employment. In this situation as well, we used the logarithm of the variable within our dataset that measured the active population of a specific village as the dependent variable and the dummy measuring the entry of Airbnb in a village as the independent one.
Therefore, the first step was to create the logarithmic variable of the active population on STATA with the following code:

"gen lnPOPattiva = ln(POPattiva)".

Having done this, one can begin with the simple regression analysis, with the two variables, dependent and independent, presented above. The STATA code used is as follows and the regression output is shown below:

"regress lnPOPattiva Dummy i.YEAR, robust".

LnPOPattiva	(1)
Dummy	0.709***
	(16.90)
_cons	7.226***
	(104.98)
Year FE	Yes
* p <0.05 ** p<0.01 *** p < 0.001	

Figure 15 Third Hypothesis Simple Regression

As can be seen from the positive dummy coefficient in the regression result, there is a positive influence of Airbnb's entry on the population that is working or actively looking for work. The result is significant at the 95% confidence interval that was used since the p-value is less than 0.05.

This was followed by the multivariate regression analysis, which means introducing the two control variables, the HCPI inflation rate and the logarithm of the variable measuring the total bed availability in a village, keeping the independent and dependent variable the same as in the simple regression case. So as to check what is the effect of adding the control variables on the previously used model.

The following STATA code was used:

"regress lnPOPattiva Dummy HCPI lnTotHospBeds i.YEAR, robust".

LnPOPattiva	(2)
Dummy	.349***
	(7.68)
HCPI	-.046**
	(-3.00)
LnTotHospBeds	.266***
	(19.85)
_cons	11.923***
	(6.06)
Year FE	Yes
* p <0.05 ** p<0.01 *** p < 0.001	

Figure 16 Third Hypothesis Multiple Regression

This last regression with the coefficient of the positive dummy variable confirms that Airbnb's entry into Italian villages has a positive impact on the working population of the villages themselves. The same comment can be repeated for the control variable measuring the availability of beds in the villages, here too the relationship is positive. The inflation rate (HCPI) is a different matter, in fact an increase in the inflation rate leads to a decrease in the working population. All three variables are significant at a 95% confidence interval, in fact the p-values lie below 0.05.

5.3 Airbnb's impact & village's key factors

In order to provide a more accurate analysis of the results, it was decided to investigate whether the impact of Airbnb's entry on the three previous dependent variables changed according to certain village-specific characteristics.

5.3.1 Accessibility

The first characteristic concerns the accessibility that the villages used for our analysis possess. Accessibility refers to the ease with which the villages can be reached in terms of proximity to an airport. Thanks to a variable that provides us with this information, it was possible to assess what influence the ease of reaching the village has on the village and how it is related with Airbnb's entry. Thus, for all three hypotheses realised, two further regression analyses were carried out in addition to those of the previous section and then compared with the results previously obtained.
The first regression analysis uses a specially created dummy variable that has a value of 1 if the distance to the village is less than 74 km (a value equal to the median of all data for this variable in our dataset) and 0 otherwise. As the main independent variable, the dummy was used in order to evaluate whether Airbnb enters the village or not and, as control variables, the same ones used previously, the natural logarithm of the total availability of beds in the hamlet and the HCPI index. Instead, for the second regression analysis, a variable called 'DxD' is added in addition to the variables described above, in which the dummy assessing proximity to an airport and the dummy measuring Airbnb's entry into the village are multiplied.

Below are the two regression analyses performed for the first hypothesis with the AVG_GoogleTrendsIndex as the dependent variable.

The following STATA code was used:

"regress AVG_GoogleTrendsIndex Dummy Dummy_Aereoporto HCPI lnTotHospBeds i.YEAR, robust"

AVG_GoogleTrendsIndex	(3)
Dummy	.349***
	(1.90)
Dummy_Aereoporto	4.577***
	(7.48)
HCPI	-1.577***
	(-5.23)
LnTotHospBeds	.863***
	(19.85)
_cons	227.671***
	(5.94)
Year FE	Yes
* p <0.05 ** p<0.01 *** p < 0.001	

Figure 17 First Multiple Regression Airbnb & Accessibility Impact on Online Visibility

Then for the second regression the following STATA code was performed:

"regress AVG_GoogleTrendsIndex Dummy Dummy_Aereoporto DxD HCPI lnTotHospBeds i.YEAR, robust"

AVG_GoogleTrendsIndex	(4)
Dummy	4.977***
	(4.97)
Dummy_Aereoporto	10.460***
	(8.57)
DXD	-7.796***
	(-5.54)
HCPI	-1.633**
	(-5.44)
LnTotHospBeds	.856***
	(4.13)
_cons	232.308***
	(6.09)
Year FE	Yes
* p <0.05 ** p<0.01 *** p < 0.001	

Figure 18 Second Multiple Regression Airbnb & Accessibility Impact on Online Visibility

As it can be observed with respect to the regression analysis without the dummy variable measuring accessibility, in the first case there is a decrease in the significance of Airbnb's entry into the villages in the online visibility: in fact, the p-value goes from a value of 0.015 to a value of 0.057. In our second analysis it is possible to see how the inclusion of the multiplicative variable between the two dummies significantly increases the significance of our analysis; in this case, in fact, both the entry of Airbnb in the village and the proximity to the airport are positively related to an increase in online visibility and both have a p-value of 0. It is interesting to note that, if taken individually, the coefficients of the variables have a positive effect on the dependent variable while their combined effect has a negative effect.

Then, the same two regression analysis were performed for the second hypothesis. The objective here is to understand how the entry of Airbnb affects the average economic income of an ordinary entrepreneur in a village. The result obtained in the multiple regression of the previous paragraph tells us that the model was not too accurate since the p-value obtained was well above 5%, the threshold used as acceptability of the model. Therefore, it was assessed whether or not the accessibility of the village impacted this economic variable with the following regressions and STATA codes:

“regress lnRedditoImprenditoreOrdCAPITE Dummy Dummy_Aereoporto HCPI lnTotHospBeds i.YEAR, robust”

LnRedditoImprenditoreOrdCAPITE	(3)
Dummy	.023
	(0.79)
Dummy_Aereoporto	.000*
	(1.000)
HCPI	-.021*
	(-2.17)
LnTotHospBeds	.035***
	(4.37)
_cons	12.567***
	(9.79)
Year FE	Yes
* p <0.05 ** p<0.01 *** p < 0.001	

Figure 19 First Multiple Regression Airbnb & Accessibility Impact on Entrepreneur Income

“regress lnRedditoImprenditoreOrdCAPITE Dummy Dummy_Aereoporto DxD HCPI lnTotHospBeds i.YEAR, robust”

LnRedditoImprenditoreOrdCAPITE	(4)
Dummy	0.255***
	(6.31)
Dummy_Aereoporto	.360***
	(7.78)
DXD	-.448***
	(-8.77)
HCPI	-1.633*
	(-2.30)
LnTotHospBeds	.037***
	(4.74)
_cons	12.362***
	(10.23)
Year FE	Yes
* p <0.05 ** p<0.01 *** p < 0.001	

Figure 20 Second Multiple Regression Airbnb & Accessibility Impact on Entrepreneur Income

The results obtained from the regression in which only the dummy variable measuring the accessibility of the village was included, confirm the result obtained earlier in fact even in this case Airbnb's entry is not significant for the average income of an ordinary entrepreneur. On the other hand, in the second regression the inclusion of the dummy variable multiplying the Airbnb dummy and the airport proximity dummy allows us to have a model capable of better explaining the variation of the dependent variable. This can be seen from the p-values of the variables, all of which are close to zero. However, it is interesting to note that even in this case, taken individually, the coefficients of the variables have a positive effect on the dependent variable while their combined effect has a negative effect.

In conclusion, the impact of the accessibility of the village was also measured, again with the same type of regression used for the other two cases, for the third hypothesis, which is how it affects the relationship between Airbnb entry and active population in the village. In the previous section, it was noted that Airbnb's entry is significantly linked to an increase in the active population. Below are the STATA codes used and the regression outputs obtained:

"regress lnPOPattiva Dummy Dummy_Aereoporto HCPI lnTotHospBeds i.YEAR, robust"

LnPOPattiva	(3)
Dummy	.313***
	(7.09)
Dummy_Aereoporto	.369***
	(10.60)
HCPI	-.037*
	(-2.39)
LnTotHospBeds	.266***
	(20.58)
_cons	10.54***
	(5.41)
Year FE	Yes
* p <0.05 ** p<0.01 *** p < 0.001	

Figure 21 First Multiple Regression Airbnb & Accessibility Impact on Active Population

“regress lnPOPattiva Dummy Dummy_Aereoporto DxD HCPI lnTotHospBeds i.YEAR, robust”

LnPOPattiva	(4)
Dummy	0.392***
	(6.42)
Dummy_Aereoporto	.500***
	(7.19)
DXD	-.174*
	(-2.16)
HCPI	-.038*
	(-2.47)
LnTotHospBeds	.266***
	(20.60)
_cons	10.642***
	(5.45)
Year FE	Yes
* p <0.05 ** p<0.01 *** p < 0.001	

Figure 22 Second Multiple Regression Airbnb & Accessibility Impact on Active Population

The results obtained confirm that in both cases the Airbnb input was significant and positively correlated with the dependent variable. A similar argument can be made for the control variable entered, that is the dummy measuring the distance of the village from the airport, which is also significant and positively correlated in both regressions. Finally, as for the other two hypotheses, it can be seen that the combination of the two dummy variables has a negative influence on the active population.

5.3.2 Culture-based Tourism

The second characteristic analysed in this study concerns cultural tourism that the villages in our dataset have. Regarding tourism of a cultural nature, it was decided to analyse the variable measuring the number of museum institutes present in the villages studied. Also in this case, the first variable created was a dummy with a value of 1 if there is at least one museal institution in the village (1 being the median of all the values that the various villages have in this variable) and 0 if there is not even one present. This newly created variable was used in the first regression that was performed. As the main independent variable in this regression model, the dummy variable measuring the Airbnb input was always used and as control variables, in addition to the dummy measuring the number of museums in the hamlets created specifically for this situation, the two variables of the previous paragraph were used: the natural logarithm of the total availability of beds in the hamlet and the HCPI index. Regarding the second regression, as for accessibility, a variable called 'DxD2' was added. This variable is always a binary variable that multiplies the dummy assessing whether there is Airbnb in the village and the dummy assessing whether there is at least one museum institution in the village. Consequently, the first two regression analyses were carried out for the first hypothesis concerning the online visibility of villages. As noted by the multiple regression performed in section 5.2, the input of Airbnb was significant for the online visibility of the hamlet itself. Below are the STATA codes used and the outputs of the regressions developed:

"regress AVG_GoogleTrendsIndex Dummy Dummy_Musei HCPI lnTotHospBeds i.YEAR, robust"

AVG_GoogleTrendsIndex	(5)
Dummy	1.752*
	(2.25)
Dummy_Musei	4.869***
	(4.65)
HCPI	-1.691***
	(-5.60)
LnTotHospBeds	.748***
	(3.51)
_cons	244.723***
	(6.39)
Year FE	Yes
* p <0.05 ** p<0.01 *** p < 0.001	

Figure 23 First Multiple Regression Airbnb & Culture-based Tourism Impact on Online Visibility

"regress AVG_GoogleTrendsIndex Dummy Dummy_Musei DxD2 HCPI lnTotHospBeds i.YEAR, robust"

AVG_GoogleTrendsIndex	(6)
Dummy	0.767
	(0.91)
Dummy_Musei	1.000
	(0.53)
DXD2	4.96*
	(2.53)
HCPI	-1.695*
	(-5.64)
LnTotHospBeds	.769***
	(3.61)
_cons	245.964***
	(6.45)
Year FE	Yes
* p <0.05 ** p<0.01 *** p < 0.001	

Figure 24 First Multiple Regression Airbnb & Culture-based Tourism Impact on Online Visibility

The first regression, with the sole inclusion of the variable "Dummy_Musei" confirms the result obtained previously and shows us how this new control variable is positively linked to the dependent variable, thus an increase in museums in the village leads to an increase in the borough's online visibility. Instead, the entry of the interaction variable between the two previous variables in the second regression leads to a considerable decrease in the significance of the two independent variables taken individually. The interaction variable has a very low p-value and has a positive value, therefore the combined effect of the two variables also influences positively the online visibility of the village.

The second hypothesis was tested with the same two regressions as before. In this situation, the dependent variable is the economic variable used previously, the natural logarithm of the average income of ordinary entrepreneurs in the borough. In section 5.2, the significance of the model was found to be quite low; so, with these two further regression analyses, it is possible to see whether there is any improvement with the introduction of the new variables. Below are the STATA codes through which the regressions were run and their respective outputs:

“regress lnRedditoImprenditoreOrdCAPITE Dummy Dummy_Musei HCPI lnTotHospBeds i.YEAR, robust”

LnRedditoImprenditoreOrdCAPITE	(5)
Dummy	.020
	(0.70)
Dummy_Musei	.055
	(1.59)
HCPI	-.022***
	(-2.15)
LnTotHospBeds	.033***
	(4.28)
_cons	12.558***
	(9.78)
Year FE	Yes
* p <0.05 ** p<0.01 *** p < 0.001	

Figure 25 First Multiple Regression Airbnb & Culture-based Tourism Impact on Entrepreneur Income

“regress lnRedditoImprenditoreOrdCAPITE Dummy Dummy_Musei DxD2 HCPI lnTotHospBeds i.YEAR, robust”

LnRedditoImprenditoreOrdCAPITE	(6)
Dummy	.0467
	(1.47)
Dummy_Musei	.159
	(2.35)
DXD2	-.126
	(-1.85)
HCPI	-.021*
	(-2.17)
LnTotHospBeds	.033*
	(4.19)
_cons	12.549***
	(9.82)
Year FE	Yes
* p <0.05 ** p<0.01 *** p < 0.001	

Figure 26 Second Multiple Regression Airbnb & Culture-based Tourism Impact on Entrepreneur Income

The first regression output confirms that Airbnb's entry into the boroughs is not significant, with respect to the decided confidence interval, compared to the average income of an ordinary entrepreneur. A similar consideration can be made with respect to the presence of museum or non-museum institutions; in fact, the p-value is also not significant in this case. In the second regression, with the intrusion of the interaction variable between the two previously used dummies, the significance of the model improves. The dummy variable of museums turns out to be significant with a positive relationship with the dependent. The interaction variable is remarkably close to the confidence interval; however, it has a negative relation to the dependent. The third and final hypothesis concerning the working population of the villages was tested in the same way. What was noticed with the multiple regression was a strong connection between Airbnb entry and the dependent variable. Here are the regression outputs with their respective STATA codes:

“regress lnPOPattiva Dummy Dummy_Musei HCPI lnTotHospBeds i.YEAR, robust”

LnPOPattiva	(5)
Dummy	.335***
	(7.34)
Dummy_Musei	.536***
	(8.89)
HCPI	-.045**
	(-2.96)
LnTotHospBeds	.253***
	(19.03)
_cons	11.876***
	(6.09)
Year FE	Yes
* p <0.05 ** p<0.01 *** p < 0.001	

Figure 27 First Multiple Regression Airbnb & Culture-based Tourism Impact on Active Population

“regress lnPOPattiva Dummy Dummy_Musei DxD2 HCPI lnTotHospBeds i.YEAR, robust”

LnPOPattiva	(6)
Dummy	.272***
	(5.45)
Dummy_Musei	.288**
	(2.70)
DXD2	.317**
	(2.96)
HCPI	-.046**
	(-2.98)
LnTotHospBeds	.254***
	(19.15)
_cons	11.96***
	(6.13)
Year FE	Yes
* p <0.05 ** p<0.01 *** p < 0.001	

Figure 28 Second Multiple Regression Airbnb & Culture-based Tourism Impact on Active Population

The results of these two regression analyses show us that in both cases the two variables, if taken individually, are significant and positively related to the dependent. The interaction variable multiplying the dummy measuring Airbnb's entry into the villages and the dummy estimating the presence of museum institutes in the villages themselves, present in the second regression, is also significant. Moreover, its coefficient allows us to state that a combined presence of Airbnb and museums increases the active population of Italian villages.

Chapter 6: Final Considerations

6.1 Conclusion

This study analysed the influence of Airbnb, the world's best-known digital platform, on Italy's rural realities, focusing on several villages scattered across the country. The analysis allowed us to highlight the variables whose values are most linked to the presence of Airbnb. Consequently, the results obtained can be used as a starting point to set up new projects and direct political decisions aimed at the entry or increase of Airbnb listings, which, as has been demonstrated, can have an important impact on several factors.

The first hypothesis assumed, concerning the growth of a village's online visibility due to Airbnb's entry into the village, is strengthened by the analysis. Both the descriptive analysis and the two econometric models show how Airbnb's entry positively influences the average value of the Google Trends Index, an indicator that measures online flows for specific words, in our case the village in question. This indicator turns out to be key nowadays, in an increasingly digitised world, for rural realities such as hamlets, which, being little known compared to large cities, can decisively exploit people's interactions by promoting their main features and events so as to increase tourism, making themselves better known.

Hypothesis number 2, concerning the positive relationship between Airbnb's entry and the economic growth of the village where the platform enters, turns out to be partly verified by our analysis. As mentioned in the section containing the descriptive results, the treated group, which saw the entry of Airbnb into their territory, has a higher increase in ordinary entrepreneurial income per capital, the economic variable used, than the control group. This result is confirmed by the econometric simple regression model; in fact there is a positive relationship between the variable measuring the entry of Airbnb in a village and the economic variable. Moreover, in this case the p-value is close to zero, so the null hypothesis can be rejected. In contrast, the multivariate regression model presents a different result. Also in this case, the relationship between the two variables presented above is always positive, but the p-value is greater than 0.05, which does not allow us to reject the null hypothesis and fully confirm the initial hypothesis.

The third and final hypothesis tested, concerning the positive relationship between Airbnb entry and an increase in the working population, that is, more people working or actively seeking work, is strengthened by the analysis. Both the descriptive analysis and the two econometric models developed confirm that Airbnb's entry increased in the active population. This is very important for rural towns, as it contributes to the prevention of depopulation in these areas by increasing employment opportunities.

This study paints a fairly clear picture of which factors Airbnb impacts most in villages, having positive effects on the local village economy. This could be the basis for identifying strategies and best practices to ensure a correct and sustainable use of the platform, so as to make the most of the upturn in tourism that has occurred in recent years. Above all, Italy, which is a country with many hidden beauties, should make the most of them by understanding where it is really necessary to invest in order to make a driving sector of the Italian economy, that is tourism, flourish more and more.

6.2 Thesis' Limits and Future Developments

The dataset used in the analysis is an extremely reliable dataset. In fact, the data in it does not derive from a questionnaire made ad-hoc for the study, but from very reliable sources, such as ISTAT, AIRDNA and the Ministry of Economy and Finance. The limitations of this thesis are mainly related to the descriptive analysis parts, where only one independent variable is used, which does not consider other effects outside the dependent variable. For this reason, it was decided to carry out multivariate regression analysis by introducing two control variables and assessing the significance of the variables in the model by taking the p-value into account.

A further area that can be improved in a future study concerns the geographical context that is considered. In fact, in this study, the analysis is carried out at the Italian level. Therefore, the implications found are specific to the country considered in the study.
As a possible future development, it might be interesting to use the NUTS1 column of the dataset that informs on the geographical area in which the village is located. In this case it would be possible to understand whether the impact of Airbnb on the dependent variable of interest is greater in the south, islands rather than in the centre, North-West or North-East.
Similarly, it might be interesting to shift the horizon of interest to a country different from Italy, but with the same rural realities to understand whether the behaviour is similar or whether there are differences. In this way it would be understood whether the value of the analysis carried out in this study are limited or the same findings can be found in other countries.

Appendix

List of Villages considered in the analysis:

	ISTAT CODE
Abbateggio	68001
Acerenza	76002
Acquasparta	55001
Alberobello	72003
Allerona	55002
Altomonte	78009
Anghiari	51001
Apricale	8002
Arquà Petrarca	28005
Arrone	55005
Asolo	26003
Atina	60011
Atrani	65011
Barga	46003
Bassano in Teverina	56006
Bellano	97008
Bettona	54003
Bevagna	54004
Bienno	17018
Bobbio	33005
Bosa	95079
Bovino	71007
Brisighella	39004
Brugnato	11007
Buccheri	89003
Buonconvento	52003
Campiglia Marittima	49002
Campli	67008
Campo Ligure	10008
Capalbio	53003
Caramanico Terme	68007
Casoli	69017
Cassinetta di Lugagnano	15061
Castel Gandolfo	58022
Castel San Pietro Romano	58025
Castel del Monte	66026
Castel di Tora	57013
Castelfranco Piandiscò	51040
Castell'Arquato	33012

Castellabate	65031
Castelmezzano	76024
Castelmola	83015
Castelnuovo di Porto	58024
Castelrotto/Kastelruth	21019
Castiglione del Lago	54009
Castiglione di Garfagnana	46010
Castiglione di Sicilia	87014
Castroreale	83016
Cefalù	82027
Cella Monte	6056
Cervo	8017
Cetona	52008
Cingoli	43012
Cison di Valmarino	26018
Cisternino	74005
Citerna	54011
Città Sant'Angelo	68012
Civita	78041
Civitella del Tronto	67017
Cocconato	5042
Conca dei Marini	65044
Corciano	54015
Coreglia Antelminelli	46011
Corinaldo	42015
Crecchio	69027
Deruta	54017
Diano Castello	8026
Dozza	37025
Egna/Neumarkt	21029
Erice	81008
Fagagna	30037
Ferla	89008
Fiumalbo	36014
Fiumefreddo Bruzio	78055
Follina	26027
Framura	11014
Frontino	41017
Furore	65053
Gangi	82036
Garbagna	6079
Gardone Riviera	17074
Garessio	4095
Gerace	80036
Geraci Siculo	82037
Gradara	41020
Gromo	16118

Grottammare	44023
Guardiagrele	69043
Irsina	77013
Laigueglia	9033
Locorotondo	72025
Loro Ciuffenna	51020
Lovere	16128
Lucignano	51021
Lugnano in Teverina	55016
Maruggio	73014
Massa Martana	54028
Mercatello sul Metauro	41025
Mezzano	22115
Mombaldone	5064
Mondavio	41028
Mondolfo	41029
Moneglia	10037
Monforte d'Alba	4132
Montagnana	28056
Montaione	48027
Monte Castello di Vibio	54029
Monte Isola	17111
Monte Sant'Angelo	71033
Montecassiano	43026
Montecchio	55018
Montechiarugolo	34023
Montecosaro	43028
Montefalco	54030
Montefiore Conca	99008
Montefiore dell'Aso	44036
Montelupone	43030
Montesarchio	62043
Montescudaio	50020
Montone	54033
Morano Calabro	78083
Morimondo	15150
Neive	4148
Nocera Umbra	54034
Noli	9042
Nusco	64066
Offagna	42033
Offida	44054
Opi	66061
Orta San Giulio	3112
Orvinio	57047
Otranto	75057
Pacentro	66066

Paciano	54036
Palazzolo Acreide	89015
Palazzuolo sul Senio	48031
Palmanova	30070
Panicale	54037
Passignano sul Trasimeno	54038
Penne	68027
Pergola	41043
Perinaldo	8040
Pescocostanzo	66070
Petralia Soprana	82055
Petritoli	109031
Pettorano sul Gizio	66071
Pietracamela	67034
Pietrapertosa	76061
Pitigliano	53019
Polcenigo	93031
Poppi	51031
Posada	91073
Pretoro	69069
Rocca Imperiale	78103
Rocca San Giovanni	69074
Sabbioneta	20054
Salemi	81018
Sambuca di Sicilia	84034
San Benedetto Po	20055
San Felice Circeo	59025
San Gemini	55029
San Giovanni in Marignano	99017
San Leo	99025
Santa Fiora	53022
Santo Stefano di Sessanio	66091
Sassoferrato	42044
Savoca	83093
Scanno	66093
Scarperia e San Piero	48053
Seborga	8057
Servigliano	109038
Specchia	75077
Spello	54050
Sperlonga	59030
Stilo	80092
Subiaco	58103
Sutri	56049
Suvereto	49020
Taggia	8059
Tagliacozzo	66099

Torgiano	54053
Treia	43054
Tremosine sul Garda	17189
Trevi	54054
Triora	8061
Tropea	102044
Usseaux	1281
Varese Ligure	11029
Venosa	76095
Vernazza	11030
Verucchio	99020
Vico del Gargano	71059
Viggianello	76097
Villalago	66103
Vipiteno/Sterzing	21115
Vitorchiano	56060
Vogogna	103077
Zavattarello	18184

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