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The impact of Airbnb on the Italian real estate market: a focus on the city of Turin.

Relatrice:
Prof.ssa Laura Rondi

Candidato:
Riccardo Abate
262402

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Abstract

This work focuses on the city of Turin to investigate the impact of Airbnb on the local real estate market. After an introduction on the sharing economy, the focus shifts to Airbnb, covering aspects such as its business model, the relationship with the hotel industry, and the regulatory issues associated with its rise in the major cities across the world. The following section concentrates on the Italian real estate market as a whole, with considerations based on data regarding both homeownership habits and market trends in terms of home ownership, the number of transactions, and prices. Once the most relevant literature regarding the relationship between Airbnb and real estate markets has been reviewed, the third chapter illustrates the data used in this work, provided by: AirDNA for listings' data, Idealista and OMI for real estate figures. Key statistics and findings are then illustrated and described. What follows is the econometric analysis, which is divided into three categories of regressions, grouped by the dependent variable specified in the model: revenues per listing, neighbourhood rent prices, and home sale prices. Therefore, the first group of regressions looks at the characteristics influencing the profitability of a listing, while the last two groups aim at investigating the impact on the real estate market. The final chapter is dedicated to a summary of the main findings and conclusions.

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1.1 The Sharing Economy

1.1.1 Definition

The term *sharing economy* is often used to describe a variety of different services, which span from the borrowing of a bike to reach the nearest tube station, to the rental of a home in Bali to go on vacation with your family. A more formal definition could be the following: "[the sharing economy is] the peer-to-peer-based activity of obtaining, giving, or sharing the access to goods and services, coordinated through community-based online services" (Hamari, Sjöklint, & Ukkonen, 2015). These goods and services are thus exchanged in what are generally called peer-to-peer markets, online marketplaces and platforms that facilitate the matching between demanders and suppliers. The first large and widely-known marketplaces of this kind were eBay and Craiglist, both founded in 1995 and for over a decade among the most successful examples of how the internet could help people find buyers for products they thought unsellable and workers for relatively small tasks no one was willing to carry out.

It is only in 2009-2010 that the term *sharing economy* started to circulate, following the creation and evolution of start-ups such as TaskRabbit, BlaBlaCar, Care.com, and Airbnb. These companies, and many others that have been founded in the following years, started to offer innovative ways to let people easily access goods and services at a lower cost, but with a significant difference compared to the initial peer-to-peer platforms. These technology start-ups grant access to goods and services mainly through creative configurations of rentals, not only via ordinary one-off purchases such as the ones taking place on eBay for second-hand goods. Also, while in traditional rental markets owners hold assets to rent them out, these start-up firms have created, among others, a new kind of rental market, in which owners sometimes use their assets for personal consumption and sometimes rent them out. Individuals offering their assets in these markets are defined consumer-owners. The most innovative aspect of such firms is embodied by their peer-to-peer nature, which indicates that the exchange occurs between individuals rather than between an individual and a firm.

Of course, some renting by consumer-owners already existed in the past, but it was mainly confined to expensive and infrequently used goods, such as vacation homes or boats, which also had longer duration rental periods. Less expensive consumer-owner goods were instead usually shared with family members or friends, often without involving explicit payments. In contrast, these new markets are open markets, and the good is "shared" in exchange for payment (Horton & Zeckhauser, 2016).

The success and the explosion of these web-based platforms have sparked the creation of different names to address the topic, the most used being: *gig economy*, *platform economy*, *access economy*, and *collaborative consumption*. These are commonly adopted as synonyms to the most prevalent *sharing economy*, which is now used to label a variety of apps and websites, often improperly. Indeed, it is right to use this terminology when introducing services such as BlaBlaCar, CouchSurfing or Getaround, where an individual decides to share (in fact, sell) a seat for a ride, his couch for a couple of days or even his car to someone for a short period. However, it is less appropriate to adopt the same terminology when referring to firms such as Etsy or Care.com, which are respectively a marketplace where small producers sell craft goods and a job-offering portal for babysitters and caregivers. The latter are peer-to-peer platforms like the former, but there is no sharing taking place, just a transaction to acquire a service or a product.

Given the above considerations, the sharing economy can be thought of as a subset of the more general peer-to-peer economy. Nonetheless, for the purpose of this work, there will not be a clear-cut distinction between the two expressions since the focus will be on Airbnb, which is a peer-to-peer platform where a physical asset, a home, is shared to offer a service (Farronato & Levin, 2015).

1.1.2 The setup of peer-to-peer markets

Firms operating in the sharing economy, and in peer-to-peer marketplaces in general, are heterogeneous and often very specific, covering many industries and sometimes employing creative business models. Regardless of the differences, peer-to-peer firms essentially have to solve the same issues to facilitate trade. These can be grouped as follows:

1. Sellers and buyers need to be matched efficiently to create a successful marketplace;
2. Exchanges are to be executed safely and trust needs to be fostered among participants;
3. Pricing mechanisms should provide the right incentives for both sides to take part in the transaction.

Matching supply and demand

To understand how companies deal with the first problem, it is important to establish that an efficient matching mechanism uses information efficiently, allowing for demand and supply to meet whenever it is possible. Moreover, the mechanism must minimize the costs associated with the transaction, which include the time spent to find a "solution" and the costs of actually having the transaction executed. It is important to point out that the extent of these costs mostly depends on the value of what is being purchased. Indeed, it is reasonable to spend a couple of hours choosing an apartment to rent for a two-weeks' vacation, but the same does not apply when booking a ride with Uber. In most cases, customers are looking for a very specific service or product, such as a ride from one city to another in a particular day or a home with a bunch of characteristics to be rented in a certain period, and there may only be a couple of sellers, among hundreds, offering the exact match. Therefore, it is important to organize the platform so that it is able to conclude the greatest number of transactions. This can be done either with centralized or decentralized marketplaces.

Peer-to-peer marketplaces adopt a centralized structure when the priority is to have low transaction costs. This is the case of the already mentioned Uber ride: it is the platform that manages the matching between a passenger and a driver, allowing the process to be faster and smoother. Decentralized markets, on the other hand, promote individual choices. They typically ask the customer to elicit a preference or a need and then allow the results to be refined through filters and options to choose from. Some platforms, like Airbnb, also require the seller to be involved, since the owner of the listing might have preferences over whom to host into his or her house and is thus required to explicitly accept the guests before the final booking takes place.

Fostering trust

The second aspect peer-to-peer firms face when setting up a market is trust among participants. In the first place, this applies to any transaction executed on the internet, since the counterparts usually do not know each other and the relationship could even occur only once. Early start-ups and e-commerce pioneers such as Amazon and Zappos.com[1] have reduced the suspiciousness of customers towards companies that only operate through a virtual shop, chiefly through a gradual development of reputation, which led to a progressive increase in the number of people willing to transact online. However, for early peer-to-peer marketplaces such as eBay, a solid reputation of the platform was not enough. Since the majority of trades occurred between peers, these websites have designed, tested, implemented and discarded several feedback procedures and rating mechanisms before adopting the most effective for their purposes. These early actors have shown that on the internet trust relies on a combination of reputation, external enforcement, and upfront inspection (Einav, Farronato, & Levin, 2016).

The first is built through reputation systems where a buyer rates a seller based on the quality of the good or service received. For some services, such as ride-sharing, the reviews can also be two-sided, so that passengers are discouraged to misbehave or it will be harder for them to find a driver. A crucial element for the process to be unbiased is to ensure that neither of the

[1] Amazon was founded in 1994 as an online bookstore, but by 1998 it expanded to other items, starting from music and videos. Zappos started to operate in 1999 as ShoeSite.com selling sneakers and shoes.

counterparts can interfere in the judgment of the other. Nonetheless, no reputational system is perfect and many of the ones currently in use present flaws and distortions.

External enforcement is generally implemented from the owner of the marketplace, and it mainly consists of tools designed to certify the quality of a seller or to guarantee buyers against bad transactions. Also, some firms impose minimum quality standards to limit entry and maintain a high level of service. This condition is related to the concept of upfront inspection, which consists of verifying the identity or the reliability of market participants. Examples of upfront inspection include Uber's criminal background checks on drivers, Getaround's "17 points of reference" screening process[2] and Airbnb's verified photo service, which is designed to bolster confidence in a listing's authenticity.

Overall, however, in online marketplaces, and particularly in peer-to-peer platforms, the general tendency is to have continuous monitoring prevail on upfront screening and selection. These procedures prevent the emergence of market problems such as moral hazard and adverse selection (Horton & Zeckhauser, 2016).

Pricing

The last element to consider when launching a peer-to-peer marketplace is, just as for any other marketplace, its value proposition. The reason why this is so important lies in what is commonly referred to as the "chicken-and-egg problem": buyers are attracted to markets with lots of sellers and sellers want to enter markets with many potential customers. Nobel Laureate Jean Tirole describes markets with network externalities, such as peer-to-peer platforms, as "two-sided markets" where both buyers and sellers obtain benefits from interacting through a common platform (Tirole & Rochet, 2003).

Hence, to overcome the hurdles stemming from a limited number of participants, platforms must design an appropriate price structure to successfully increase the market-base. Price structures differ substantially from market to market, since product categories bearing two-sided market attributes range from credit cards to newspapers, gaming consoles, and operating systems (Rysman, 2009). The examples cited apply unusual and differentiated pricing strategies, despite the fact that network externalities apply to both buyers and sellers. For instance, credit card issuers essentially pay customers to use their credit cards through loyalty schemes and rewards, while it is businesses that have to pay for adopting the service. On the opposite side, developers working for the Windows operating system are subsidized because consumers are willing to pay a mark-up for a high degree of developer participation. That happens because the pricing on one side of the market not only depends on its specific demand but also on how this demand affects participation, thus supply, on the other side; it is only through a successful engagement from

[2] From the platform's website: "Every Getaround driver must pass a thorough trust and safety screening to verify their identity, credit history, and clean driving record. Our process involves 17 points of reference including Facebook, and the Department of Motor Vehicles". (https://www.getaround.com/tour/safety)

both sides that profits can be made. Since the participants on both sides in peer-to-peer platforms are mostly ordinary people rather than companies, the problem is even more challenging.

One of the first mechanisms eBay devised to attract sellers and have them list their products consisted of creating virtual auctions online. The system was appealing because it allowed prices to better reflect the real demand for a certain product, which often meant having selling prices exceeding a seller's original estimate. Similarly, in its first five years of activity, Taskrabbit used a mechanism where contractors were bidding to "obtain" a task posted by a customer. However, the process was inefficient and the company discarded it altogether in favour of a Uber-like matching system where customers decide the contractor they prefer based on their hourly cost and experience (Taskrabbit, 2014). Indeed, auctions are no longer popular in peer-to-peer marketplaces, mainly because of their time-consuming structure and an increase in competition.

An alternative to auctions is to let sellers set prices autonomously, and this is what happens on websites such as Etsy or Care.com. On other platforms, Airbnb for example, the sellers are free to choose what to charge, but the website generates a price range suggestion based on the prices of other hosts and the actual market demand. Putting hosts in competition by telling them what others are charging is useful to keep prices low while also maintaining high levels of quality.

An additional pricing mechanism is the one adopted by some peer-to-peer lending start-ups[3], where it is the platform itself that determines the interest rate a lender should earn from a specific borrower. Based on the amount of risk a lender is willing to take, the algorithm evaluates a borrower's credit-worthiness and enables the transaction.

Another way to attract both sellers and buyers on the platform focuses on lowering the costs a seller has to bear to set up and advertise his business or product. The result is clearly visible on Airbnb, where anyone can easily make money posting any type of listing, and this leads to having some very unusual listings, from tree-houses to castles in the middle of nowhere. A further implication concerns supply flexibility: since it is inexpensive to get on and off the market, the number of listings has a significant increase when demand grows.

Uber has yet another pricing mechanism, which increases prices, and as a consequence driver rates, through its surge price algorithm: during periods of peak demand price increases reach the marginal utility of drivers that would otherwise keep off the market (Einav, Farronato, & Levin, 2016).

It is worth stressing that the main issues expounded above must be addressed in any type of peer-to-peer marketplace, whether the platform is centralized or decentralized, whether the role of buyers and sellers is distinct or not.

3 Lending Club and Upstart for instance.

1.1.3 What sharing economy companies have in common

Going back to the companies operating in the sharing economy, it is interesting to look at their common features. The first one is the period during which many of them were founded: between 2008 and 2010 (The Economist, 2013). In fact, it seems that the emergence of the sharing economy has been fuelled by the global financial crisis, which triggered a change in attitude towards ownership. A preferred alternative is access to goods and services, which can come in the form of subscriptions, rentals, leases, reselling and through swapping.

Other factors that contributed to the explosion of the phenomenon are the diffusion of smartphones with an internet connection and a GPS, urbanisation, new consumer needs, and greater attention to the environment and to the efficient use of resources. As a result, any start-up or company that is part of this trend relies on at least one of these elements and, whatever the business model, the main features are:

- **Sharing-based**
  Users share assets, resources and services with others for either long or short periods of time. Consumption becomes collaborative: the internet is making it easier and cheaper to aggregate and match supply and demand.
- **The exploitation of idle capacities and resources**
  Many goods are idle most of their time (think of cars or second homes); the goal of the sharing economy is to allow others to benefit from this idleness in exchange for money.
- **On-demand access**
  The underlying idea is to use a product or a service only when it is needed, paying a proportionate amount of money for its use. As a result, costly items are going to be purchased only by those who will frequently use them.
- **Increased personal interactions**
  The sharing economy connects people and is strongly dependent on trust. Platforms can be seen as communities of strangers with shared values who decide to cooperate under shared rules and norms. Feedback systems help to evaluate and maintain the reputation of participants.
- **Drive towards sustainability**
  Consumers increasingly prefer sharing rather than owning, not only to save costs but also to increase the useful life of products. Growing attention regarding buying habits has gotten people more conscious of environmental matters arising from unnecessary purchases.

Even if many of them started mainly as peer-to-peer platforms, sharing economy companies can be distinguished for their business model, either consume-to-consumer (c2c) or business-to-consumer (b2c). For the former, Uber and Airbnb are the most successful examples, while Zipcar and bike-sharing services belong to the latter. However, the difference between c2c and b2c platforms is not too important if compared to traditional (non-sharing-economy) firms, since both lower transaction costs and provide individuals with tools previously available only to firms.

This way, peer marketplaces create more liquid markets where a large number of people are able to either monetize their assets or access services at a lower cost. As already mentioned, this is possible thanks to spot transactions, nimble certification and feedback systems, and, in some cases, regulation skirting.

1.1.4 The impact of the sharing economy

A 2015 study by PwC, a consultancy, estimates that by 2025 sharing economy companies operating in five key sectors where the business model is going to be more prevalent (travel, car-sharing, finance, staffing, and music and video streaming) will earn sales revenues of up to $ 335 billion, compared to $ 15 billion in 2013 (Bothun, et al., 2015).

Of course, these innovations are set to have a higher impact on some industries than others, but it is only a matter of time before even the most traditional businesses will be affected. A related study by PwC identifying 7 sectors where this transformation is already taking place includes, in addition to the ones mentioned above, the energy and the retail and consumer goods sectors (Osztovits, Kőszegi, Nagy, & Damjanovics, 2015).

The innovations already taking place in these industries are providing equalizing benefits both on the demand and the supply side (McGinnis, 2018). On the demand side, consumption is becoming more broadly distributed, letting the middle classes have access to services and goods that were once available only to the rich. The key players enabling this transition are online agents, who reduce transaction, agency, monitoring, and search costs and essentially act as the intermediaries that have long been used by the rich to have access to personalized goods and services. Given that a larger and more diversified population can now access these services, the sharing economy is also reducing the differences in the quality provided to higher and lower-income groups.

The supply side, on the other hand, is creating markets for human and “property” capital, which can now be monetized on the spot even from people with modest skills or assets. Since a disproportionate share of the assets owned by the middling classes is made up of either human or property capital, the sharing economy is providing extra sources of income, and opportunities to diversify, that in the past were a prerogative to the upper classes only. Also, these new sources of income are extremely flexible, meaning that an Uber driver has no obligations to work under a strict schedule and can make the best use of his time.

Another aspect characterizing the sharing economy concerns the “enlivening of capital”. Hernando De Soto showed that poor people in the developing world stayed poor partly because they did not enjoy formal property rights. However, the introduction of such rights allows the poorer to accumulate wealth through access to mortgages and other instruments. Similarly, according to Calo and Rosenblat (Calo & Rosenblat, 2017), information technology enlivens the capital of the middle classes in the developed world.

Not only private individuals exploit the sharing economy and its benefits. In fact, many businesses and corporations are making use of these services to reduce their expenses or facilitate the work of their employees. Certify, a travel and expense report management software, in its 2019 report on travel and expense management trends, shows that for example, Uber is the most expensed company in the ride-hailing category, by far in front of taxis. Other services expensed by company employees include scooter rentals such as Lime and Bird or meal delivery services offered by firms such as Uber Eats or Grubhub (Certify, 2019). In addition to that, Airbnb states that over 700,000 companies have booked with Airbnb for Work (previously named Airbnb for Business) since the service was launched in 2014 (Airbnb, 2018). This helped companies save on expenses, since around 60% of these bookings involved more than one guest.

While estimating the entity of revenues earned by sharing economy companies is possible and relatively easy, it is a lot harder to assess the impact of the sharing economy on GDP thus far. Researchers that tried to estimate these figures point out that in some cases the impact could even be negative, since the equalizing effect of the sharing economy taps on unused assets that have already been produced and sold. As the World Economic Forum puts it, making better use of unused assets expands supply and brings prices down, increasing the option value and consumer surplus but none of these consequences is taken into account in the measurement of GDP (World Economic Forum, 2016). Hence, these adjustments are yet to be made, and they are going to be fundamental if the sharing economy will continue to replace and add to existing economic activities.

1.1.5 Further developments

The innovations and the shifts in attitude of people towards the sharing economy may seem profound and very important, but they are actually just at the beginning. Thinking about the long-term effects of the sharing economy and peer-to-peer markets, there is still a lot to be disrupted. One aspect that often goes unnoticed when discussing these phenomena is that companies across the majority of industries typically adopt business models built on consumption and ownership of goods. The sharing economy will challenge these paradigms and force companies to adapt, lest their collapse.

Disruption may come in two forms: a lower aggregate demand or demand for a different type of goods. Firms operating in the accommodation and transportation industries, for example, are set to be among the most impacted. A 2016 study from the University of Berkeley on the impact of car2go in the United States suggested that for every vehicle in the fleet of the car-sharing service, about 7 to 11 privately-owned cars have been taken off the streets of the cities where the service is active (Martin & Shaheen, 2016). Carmakers are well aware of this phenomenon and it is no coincidence that car2go was created by Daimler, the parent company of Mercedes-Benz. Other car manufacturers have expanded their business portfolio to these services: BMW in 2011 launched DriveNow, a premium car-sharing service, in a joint venture with Sixt, a car rental company. DriveNow and car2go merged in 2018 to provide essentially the same service under the name of ShareNow, demonstrating the importance of scale and the strong competition in the car-sharing market.

On the other hand, incumbent companies can preserve their business models yet adapt their products, or develop new ones, based on the needs of the sharing economy. For instance, cars might be designed to satisfy a different type of use, with manufacturers installing special locks to facilitate the opening of the car should it be shared with someone else via an app (Horton & Zeckhauser, 2016).

The reason why many of the examples described involve cars lies in the threat that the industry faces from the previously mentioned disruptions, since it is the best example of underused high-value item. With time, the sharing economy will spread to less valuable items as well, but the extent of this expansion will be based on a few crucial characteristics, because sharing low-value and poorly durable items is both inefficient and useless. The items more likely to be shared are thus luxury and designer items like clothes or pieces of furniture that can be either rented or resold. Another category may be expensive sports equipment, which is often no longer useful to professional athletes but can be used by amateurs. Even if sharing (or second-hand markets) already exists for these items[4], technology will help lower transaction costs and other hassles related to organizing the exchanges, letting more people have access to them. If this expansion catches on, companies might find discover that customers are willing to spend more for products that have a higher durability or if it is possible to recoup part of the original value.

The last aspect to consider when thinking about the long-term evolution of the sharing economy concerns regulation and changes to legal systems around the world, since they have been shaped around an idea of ownership that may no longer apply to new ways of using objects.

1.2 Airbnb Overview

This section will focus on Airbnb, the largest, most successful and most popular website for short-term rentals. Starting from its history and business model, there will be a review of the literature concerning its impact on the hotel industry and the regulatory disputes it has been subject to.

[4] Spinlister (https://www.spinlister.com) for example is a platform for sharing sports equipment, while Rent the Runway (https://www.renttherunway.com) is focused on dresses and accessories.

1.2.1 History

The story of Airbnb begins in 2007, when Brian Chesky and Joe Gebbia decide to set up a website to rent a few beds in their San Francisco loft during the annual Industrial Design conference, a major event taking place in the city during which hotels are fully booked.

The initial idea was to earn some extra money to help them pay the rent since they recently moved from New York to San Francisco and were both unemployed. The original name of the website was "Airbed and Breakfast" and the concept was very simple: they would provide guests an airbed, breakfast and, if they wished, tours of the city. Their first visitors were two men and a woman who paid $80 each to sleep on the air mattresses. As soon as the two founders realized the potential of the idea, they included their friend Nathan Blecharczyk in the founding team and started working on the development of the start-up, launching different editions of the website before it came to the attention of a sufficient number of people.

Almost a year after the first guests, the trio launched the website for the third time during the Democratic Convention taking place in Denver, in August 2018. They manage to achieve over 80 reservations through a variety of hosts who either listed bedrooms or airbeds to strangers. The week following the convention reservations are back to zero and the founders realize that the idea of sharing mainly airbeds is not cool enough to constantly attract a considerable number of people. In March 2009, after the introduction of some new features, the start-up changes its name into "Airbnb" and becomes the platform everyone knows, expanding beyond just rooms to entire apartments, houses, and other properties (Hoffman, 2015).

Since 2007 Airbnb has hosted over 750 million people and it is currently present in more than 18,000 cities and 191 countries, with a number of listings exceeding 7 million (Airbnb [1], 2020) and revenues of $ 1.1 billion in the last quarter of 2019 alone (Newcomer, 2020).

1.2.2 Business Model

Airbnb is a peer-to-peer platform for short-term rentals where hosts post listings consisting of beds, rooms or entire properties and guests book them for the number of nights they need. Prior to considering how the platform makes money, it is appropriate to examine Airbnb's business model through the so-called "business model canvas", a template created by Alexander Osterwalder in 2005 to evaluate and investigate innovative start-ups and firms. The template rests on 9 pillars, which cover and extend the main characteristics regarding the infrastructure, offering, customers, and finances of the firm.

- **Key activities**: these are the most important activities for the firm's operations and play a crucial role in value creation for the customer. The main ones include platform development, sales and marketing, customer service, the creation and maintenance of supply and demand matching mechanisms, management of bad behaviour and sensitive information protection.

- **Key resources**: essential assets for the company to sustain its business model and acquire new customers. For Airbnb these include the platform itself, the properties listed on the website and the sense of community created through the interaction between the hosts and the guests. Also, employees ranging from software engineers to customer support staff play an important role for the company.
- **Key partners**: this pillar refers to the alliances a company has to stipulate to offer a better service. Airbnb's partners are essentially the hosts that decide to post listings or experiences on the platform, the venture capitalists that provide funding to the company until it becomes profitable and other actors that play a more operational role, such as the insurance companies and the professional photographers.
- **Value propositions**: these are the elements that distinguish a company from its competitors. Airbnb has to have two distinct sets of value propositions, one for the guests and one for the hosts. The platform lets hosts earn relatively easy extra money with extreme flexibility thanks to the efficient matching of supply and demand. On the other hand, guests have a safe access to unique properties and experiences without the strain of having to spend a lot of time searching for them.
- **Customer segments**: they are the type of customers a company chooses to serve, offering products and services that satisfy their needs. Hosts and guests can be considered as the two main customer categories for Airbnb, which are then divided into different segments depending on their characteristics. At the beginning most of the guests were young and dynamic individuals who wanted to spend little money to find an accommodation. Over time listings became more differentiated and other type of customers are now sought after. For example, the firm is currently trying to establish itself in the business travel segment and in the higher-end vacation rental market.
- **Channels**: how a company reaches its customers and delivers its value proposition. The main channels for the platform are its website and its mobile app, through which potential customers browse listings. Other channels include the websites and blogs where the company advertises and promotes its services to both hosts and guests.
- **Customer relationships**: these can be grouped in three different types of relationships. The first concerns the acquisition of new customers, the second how to keep current customers and the third how to grow revenues from existing customers. Airbnb maintains relationships through its customer service function and earns the trust of customers through its review mechanisms. It is important to note that the platform works as a self-service, minimizing the interactions needed between a customer and Airbnb.

- **Cost structure**: this pillar describes the cost structure stemming from the business model adopted by the firm. The cost structure of Airbnb involves three main cost categories. There are costs related to the platform's infrastructure (including employees' salaries), customer-related costs (which include marketing, sales, customer acquisition and processing fees), and administrative costs (arising from regulations, legal compliance and insurance policies to protect the properties of the hosts).
- **Revenue streams**: essentially, how the company makes money. Airbnb earns mainly from the fees paid by hosts and guest. The first generally cover transaction processing costs (3-5%), while the fees extracted from the customers are higher (up to 20%) and depend on variables such as length and period of stay, type of listing booked and others. Revenue also comes from fees on additional peer-to-peer services available on the platform, such as Experiences or Adventures.

Exhibit 1 shows the Airbnb business model canvas created by Business Strategy Hub, a website focusing on business strategy and analysis. It is important to highlight that Airbnb considers both hosts and guests as customers. Indeed, hosts have to be attracted to the platform just as it happens with customers since competition from websites offering similar services, such as Booking.com or HomeAway (owned by Expedia), is fierce. This is because a greater number of hosts on the platform provides a higher diversification for listings and a wider selection, which in turn lead to more guests and higher revenues.

Browsing the platform's website, one can easily see the importance Airbnb devotes to hosts and how straightforward it is to become one. Indeed, the founders have always put great emphasis on the facility of sharing a home and, just like Jobs wanted the iPod to always be 3 clicks from a song, prospective hosts visiting the website for the first time are 3 clicks from sharing their home while potential guests are 3 clicks from making a booking. Another important feature is the company's clarity on the fees hosts are going to pay and on their rights, which include insurance up to a million dollars for property damages.

A distinguishing trait belonging to the hosts who have listings on the platform concerns their "loyalty", which is uncommon in the digital world. When someone uses the internet to advertise their product or service (for instance a home to rent, or a used car to sell), and there are multiple platforms allowing this to happen, the tendency is to use as many of these websites as possible to reach a greater audience and achieve the desired outcome (for example the sale of a used car). This is made possible from the low marginal costs of creating multiple accounts to place the same listing on multiple platforms. However, Airbnb hosts tend not to engage in such practices and their rentals appear on that platform only (The Economist, 2017). This means that the value proposition, the customer base, and the brand identity of the firm are strong enough to provide considerable business to hosts, without them needing alternative channels to monetize their assets.

Generally, the process leading to a booking on Airbnb starts with a host creating his profile and adding a listing on his behalf. Once the platform verifies the authenticity of the listing, it is publicly available to be booked. A potential guest browsing the website finds the listing along with others that suit his needs but, before one of these actually becomes a reservation, the guest needs the approval of the host. Hosts typically reply in a period ranging between two to forty-eight hours, so the potential guest checks out on the first listing on which he is accepted, finalizing the transaction. A work by Fradkin (2017) points out that, on average, 42% of requests are not accepted and, for this reason, potential guests often submit more than one. Once the period of the stay ends, Airbnb asks the guest to leave a review on the stay.

The business model can be summarized with the following diagram:

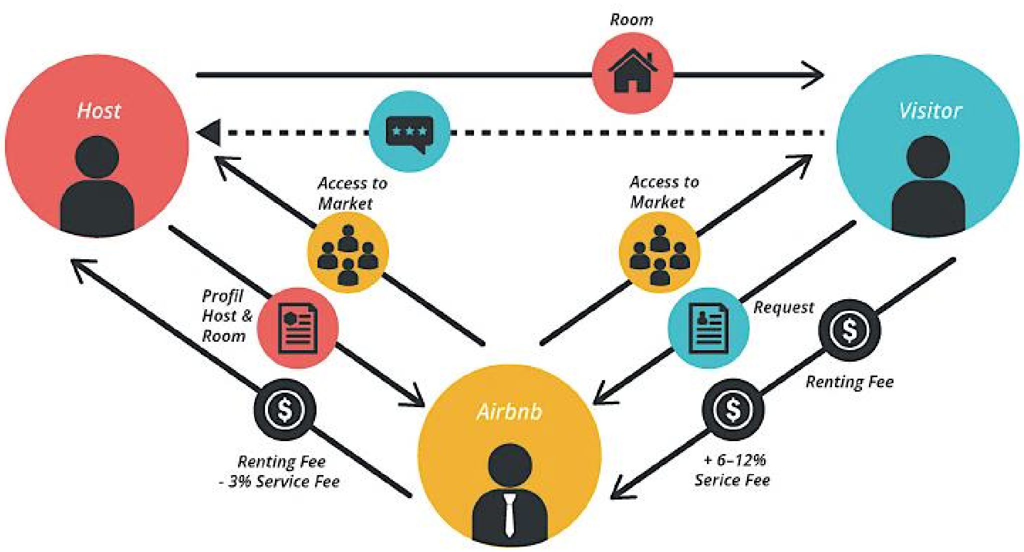

Figure 1.1. How Airbnb works. (From: https://bmtoolbox.net/stories/airbnb/).

Over the years the company extended its business to other peer-to-peer offerings. These come in many forms, starting from the so-called Experiences, which usually include tours of cities or regions but also cultural activities like cooking, painting, and many others. The hosts of experiences are typically ordinary people with particular interests or skills that organize small groups of people to carry out these activities. In 2019 the Experiences offering has been expanded with another product: Airbnb Adventures. The firm describes the choice as a way of "democratizing the adventure market", which an estimate by the Adventure Travel Trade Association valued at $ 683 billion in 2017. Those offered to Airbnb guests are mostly trips to exotic locations hosted by local experts, following Airbnb's mantra of living like a local and discovering the world by experiencing it.

While these products can still be considered close to Airbnb's original vocation, the same does not apply with "Business Travel Ready" (BTR) properties. This category of listings was launched in late 2015 (Dillet, 2015), when the company unexpectedly decided to enter the business travellers' market, until then a segment lightly impacted by the sharing economy. The idea was to categorize some properties as suitable for business travellers and to eventually establish partnerships with companies whose employees are often on the move. Airbnb's definition for BTR rentals initially encompassed specific characteristics such as:

- Hosts that reply within 24 hours;
- Ratings greater than 4.5 for cleanliness, location and check-in process;
- Internet access, a washer and a dryer.

The definition of BTR properties has now been dismissed in favour of "business-friendly" properties, for which slightly different criteria apply. These include high overall ratings, at least one business review, and the presence of a smoke detector and a carbon monoxide alarm in the house[5]. Business travellers can easily find homes and boutique hotels matching the criteria by selecting the "work trip" filter when searching for accommodation. Even if results have been disappointing thus far, the company still believes there are great opportunities for the business travel segment.

Besides the introduction of activities such as Experiences and business-friendly properties, the company has also launched the product categories of Airbnb Plus and Airbnb Luxe. The first is essentially a label assigned to properties that satisfy strict quality requirements, which are periodically inspected by Airbnb staff. Airbnb Luxe, on the other hand, is the most exclusive service that can be found on the platform: it lets guests book castles and other exclusive properties can be considered as an upgrade

The idea is that guests book exclusive properties such as castles and historical villas and a dedicated "trip designer" plans every detail about the holiday, from the airport transfer to the restaurants and locations to visit. These properties are also provided with staff that can include chefs, waiters, and others, similarly to what happens for upscale hotels. In fact, the platform's intentions include the penetration of the high-end accommodation market segment to provide an Airbnb-like refined experience to guests. Know-how and reputation are important to thrive in these market niches. For these reasons Airbnb is seeking the support of concierge companies and acquiring smaller competitors, among them the company Luxury Retreats, bought in early 2017 for $ 300 million.

1.2.3 The Impact on Hotels

Since its early stages, Airbnb sought to provide accommodation for those who could not find or afford a hotel. Over time, the platform expanded to provide a different set of services and to create a different concept for accommodation, but the hotel industry continues to be seen as the most impacted by its growth. However, a section on Airbnb's website[6] states that 74% of Airbnb properties lie outside the main hotel districts and that 79% of their guests want to visit or stay in a specific neighbourhood since over 90% of their guests want to "live like a local". These

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[5] More criteria can be found at: https://www.airbnb.com/help/article/1185/how-do-i-search-for-a-place-to-stay-when-i-travel-for-work

[6] These figures can be found at: https://www.airbnb.com/economic-impact

statements are clearly aimed at rejecting the critics of the hotel industry and at claiming Airbnb's identity as a different service from the one offered by hotels; yet, is it the truth? Several studies and researches have been conducted to investigate the impact of the platform on hotels, especially in the USA, where the early adoption of the platform allowed for longer time series and effects to be analysed.

A paper produced by Zervas, Proserpio and Byers (2016) investigates the impact of Airbnb on the hotel industry focusing on the platform's entry in the state of Texas. The initial hypothesis of the authors predicts that a portion of the stays booked on Airbnb are substitutes for hotel stays, thus necessarily having some kind of impact on hotel revenue. They also hypothesize that the impact depends on the market segment of the hotel, its location and the period of the year. It is worth mentioning that Airbnb's growth and adoption in the state of Texas have not been the same everywhere. In fact, the distribution of listings is not as homogeneous as hotel presence: less populated areas have fewer listings compared to metropolitan and major urban areas.

One of the first results obtained by the authors concerns the effect of a 10% increase in the supply of hotel rooms and Airbnb listings. A 10% increase in the number of hotel rooms is estimated to dent 1.6% of hotel revenues throughout the state of Texas, while a 10% rise in Airbnb supply leads to a 0.39% decrease in revenues. This difference is explained by the fact that not all Airbnb stays act as substitutes for hotel stays.

Considering more specific impacts, the study reveals that the most affected hotels are independent hotels, while chain hotels, perhaps thanks to reputation, loyalty schemes and stronger marketing strategies, are less hit. Also, by taking into account the total surface dedicated to conference and meeting rooms to identify business-friendly hotels, the authors discover that these are less impacted as well. Overall, coherently with Airbnb's initial positioning as a "casual stays" provider, the negative effect on hotels increases when considering cheaper and less fancy hotels.

The most interesting finding concerns the period during which the number of Airbnb listings surge. Just as one would expect from a sharing economy platform, the offer of listings on the website is extremely flexible and uneven throughout the year: the number of people willing to become hosts increases during periods of peak demand, also thanks to the higher prices they are able to charge. Airbnb can thus cope with peak demand by instantaneously raising prices and increasing supply, while hotels can only employ the first type of response. Predictably, the outcome stemming from Airbnb's hike in supply leads to lower prices during the peak. Focusing on the SXSW festival taking place in Austin every year, the authors estimate that the impact Airbnb has on hotel revenue is approximately 1.5% higher during this period, proving that the effect varies depending on the period of the year. Moreover, Austin is the city where the adoption of Airbnb has been the highest in Texas, with a cumulated revenue drop amounting to approximately 10% over a five-year period.

Since hotels rely on a business model built on a fixed stock of capacity (the number of rooms), most of their profits are made by having wide price swings, thus charging higher prices, during periods of peak demand. Indeed, the capability of Airbnb to scale supply almost instantaneously without incurring significant marginal costs makes it an unusual competitor for hotels, which see their pricing power reduced during these periods. In the long-term, the influence of such platforms could therefore prompt a strategic response from hotels, perhaps in the form of diminished investments or even market exit. The process of designing, approving, building, and opening new hotels is a lengthy one and can take up to 4 years in the United States. Also because of this, the period taken into account for the analysis of Zervas et al. failed to yield any significant results regarding Airbnb's influence in the choice of long-term strategies for new hotel projects.

However, a working paper by Farronato and Fradkin (2018) predicts that in the long-run Airbnb supply will significantly differ depending on the city. The number of hosts should be higher in cities with higher prices, occupancy rates and demand variability, but lower hosts' marginal costs are also expected to influence the decision. These costs include the perceived danger of hosting strangers in one's home and tend to be higher for people who do not live on their own or have children. Considering the short-term, the authors show that in cities where hotel capacity is constrained, Airbnb has the effect of reducing prices more than occupancy rates, thus increasing competition and impacting the hotel industry's policy of charging significantly higher prices during periods of peak demand.

Similar insights have been presented in a more recent work by Hui Li and Kannan Srinivasan (2018). Starting from the assumption that seasonality is the main component influencing the hotel industry, the authors find that the entrance of Airbnb in a specific market helps prevent an excessive increase in accommodation prices during high-demand periods, while also having a positive effect for demand. This happens because a larger supply leads to lower prices for both hotels and Airbnb listings, which as a result attracts more people, recovering the "underlying demand". Using data from 8 major US cities, it has been estimated that hotels' pricing policies during high-demand periods reduce underlying demand by approximately 13.7%. The surge in Airbnb listings during these periods is thought to be able to recover up to 67.5% of this lost demand, but the adoption of a seasonal pricing policy from Airbnb itself cannibalizes this recovery. Therefore, only about 34.3% of the underlying demand is recouped.

Evidence of Airbnb expanding the market rather than simply cannibalizing hotel demand has been documented by Farronato & Fradkin as well (2018). The authors find that many of the travellers that have booked a stay through Airbnb would not have done the same if only hotel rooms were available. The proportion of such guests is estimated to range from 27% to 34%, but when taking into account capacity constraints and prices, the percentage of Airbnb guests who would not have booked a hotel room had Airbnb not been available can climb up to 63% (as is the case for the city of New York).

How can hotels cope with these issues? Li & Srinivasan provide a recommendation for tackling Airbnb's presence: the adoption of a less seasonal or even a counter-seasonal pricing policy. The rationale behind this strategy leverages on the fact that Airbnb supply is lower during periods of low demand, making it is easier to keep prices high to the detriment of clients who have fewer alternative choices. This strategy is predicted to be more successful in markets where Airbnb penetration is higher and its supply elasticity is stronger, but no evidence of its adoption has been found.

The rest of the findings from Li & Srinivasan's study are in line with the work from Zervas et al.: Airbnb has a more negative effect on low-end hotels, in cities where the seasonality of demand is higher and the percentage of leisure travellers is higher. The share of leisure travellers is particularly relevant because of their price sensitivity and the seasonality of their demand, which is why hotels catering to business travellers are once again found to be less affected. However, as Airbnb is increasingly targeting business travellers (through BTR properties before and business-friendly homes now), higher-end hotels will eventually find themselves in a more challenging situation. In 2016 Airbnb estimated that 10% of its bookings were work-related (The Economist, 2017), a figure which may seem relevant at that time. Unfortunately, the company's efforts to attract a greater number of business travellers have not yielded sufficient results, partly due to how Airbnb stays are perceived. Business travellers' lower valuation for Airbnb stays may arise from the uncomfortable feeling of occupying a room in a property where someone else is living or the absence of certain facilities needed during their stay. Both of these are behind the introduction of the "Business Travel Ready" program described in 1.2.2.

The largest hotel groups are well aware of the disruption brought by platforms such as Airbnb, and some of them have started taking the first steps in the direction of adjusting and expanding the portfolio of services offered to their customers. Since home-rental platforms are slowly becoming more like hotels, the latter are reacting by offering Airbnb-like services, in a trend that is set to blur the boundaries between the two groups of businesses. For example, Marriott International, the world's largest hotel group, has been the first to launch the so-called "extended stays solutions", which are essentially more spacious hotel rooms with full kitchens, spaces to work and relax. These can be found in hotels completely dedicated to extended stays as well as in hotels where most of the rooms are conventional and some are not.

Extended stays are a sort of in-between solution to deal with peer-to-peer players by converting some conventional hotel space to experiment new products. However, the breakthrough came when the Marriott hotel group started testing a luxury and premium home rental service named "Tribute portfolio Homes" in 2018, before launching it on a larger scale in 2019 under the "Homes & Villas" name (Marriott International, 2019). The service is clearly a response to Airbnb Luxe (see 1.2.2), and its rentals now include over 2,000 private homes in more than 100 destinations worldwide. They are managed pretty much like Airbnb, with the difference that Marriott relies on professional home management companies to make sure the quality standards requested by its customers are met. Like Airbnb, these are private properties belonging to people who are often away from home or hardly-used second homes ranging from castles to apartments and cottages. Not only Marriott, also AccorHotels is leveraging on its brand to position itself in the premium tier of the home-sharing business, with a home-rental service bearing the name "Onefinestay", and the same is happening with Four Seasons' "Private Retreats" rentals.

1.2.4 Regulatory Issues

Hotel groups have until now mostly dismissed concerns that Airbnb is threatening their businesses, typically replying that business travellers represent their core and per-to-peer platforms are struggling with them.[7] However, the initiatives described in the previous paragraph reveal a different story, one where the hotel industry, especially in the US, is confused, worried, and lacks a clear strategy to stand up to the new competitor.

Paying attention to the statements of the American Hotel and Lodging Association (AHLA), to which Marriott, Hilton and Hyatt belong, it is evident that in the year 2016 the industry has also started lobbying activities to address its worries. The industry's efforts were, and still are, aimed at obtaining a regulation for the so-called "short term rental" (STR) platforms. The group argues that Airbnb is *de facto* operating as a hotel group but playing with different rules, penalizing other hotels, their labour force and the people living in the surroundings of its listings (Benner, 2017). Hotels are mainly affected due to zoning regulations, safety requirements, and the collection of lodging taxes, none of which applies to Airbnb (except for city-specific requirements that are to be discussed afterwards). The absence of such obligations, in the words of hotel groups, eliminates the level playing field that should lie between what essentially are two competitors in the same business. Other issues brought to the attention of the authorities concern the effects that Airbnb is having on the cities where its penetration is high, which are believed to entail a rise in rents ad house prices as well as negative externalities caused by the presence of tourists in residential areas.

For these reasons, the AHLA is striking alliances with politicians, neighbourhood associations, affordable housing groups and hotel labour unions. But how much can hotels rely on lobbying to obtain rules designed to weaken Airbnb and preserve their business? According to Li & Srinivasan (2018), the introduction of regulations that increase the cost of hosting on Airbnb have a positive effect on hotel profits, but only up to a certain level. The consequences are estimated to vary depending on the type of hotel, with higher-end ones being the most advantaged. Nonetheless, even if regulation helps hotels reduce losses in profitability, their vulnerability to Airbnb persists.

Pressure from hotel lobbies certainly played a significant role in bringing to light the downsides of Airbnb's rapid diffusion, but most policy adjustments, especially city-specific rules, came after the mobilization of interest groups reporting a variety of complaints by citizens. Coherently with Airbnb's philosophy of "living like a local", guests often prefer to find

[7] To say it in with the words of a Marriott executive in late 2016: "[Airbnb is not] really making headway in the corporate environment, which is really our bread-and-butter business". From: https://www.nytimes.com/2017/04/16/technology/inside-the-hotel-industrys-plan-to-combat-airbnb.html

accommodations outside the main tourist districts, in residential areas. The choice not only depends on price but rather on the idea of being a traveller living the different aspects of the city rather than a tourist hunting for historical landmarks and monuments. Airbnb takes pride of these aspects, asserting that its guests spend more than double the amount spent by typical tourists, and that 42% of these expenses occur in the neighbourhoods where they stayed (Airbnb [2], 2020), thus supporting local businesses and revitalizing neighbourhoods. Put it this way, it may seem that Airbnb, even considering the advantages it exploits by not being a conventional accommodation facility, helps redistributing the economic benefits of tourism. Nevertheless, critics lament that also the social downsides of tourism are being redistributed, to the detriment of residents and locals. Namely, complaints involve two type of issues: a perceived increase in home prices and rents, and negative externalities involving the quality of life.

The first problem rests on the assumption that every housing unit listed on Airbnb is essentially a home taken off the market, be it the long-term rental market or the sales market. An increase in the number of entire homes listed on the platform is believed to negatively impact housing availability and affordability. This leads to gentrification[8], because investors buy up properties to permanently rent them on the short-term market, pushing locals out of their neighbourhoods to find more affordable places to live. More insights regarding this phenomenon and its consequences can be found in Chapter 2, where academic research and literature examining these aspects is presented.

The second type of complaints involve the annoyances locals have to withstand once their neighbourhood becomes a 'urban tourism' destination. Neighbours of properties listed on Airbnb lament the fact that guests tend to be noisy, the uncomfortable feeling of having strangers around their home and a no longer existing sense of community.

One of the aspects on which regulators determine how to decide whether a rental should be or should not be regulated concerns the format of the rental itself, during which the host may be either present, temporarily absent, or permanently absent. Many cities have decided not to regulate the first type of rentals while, since they are more likely to behave like hoteliers, occasionally and constantly absent hosts have been the primary objectives. The approaches adopted by regulators in Europe and North America essentially fall into three categories (Nieuwland & Van Melik, 2018): total prohibition, partial restrictions, and *lasseiz-faire*.

Prohibition approach

The most drastic decision a regulator can make involves the unconditional banning of STR platforms in a certain area, be it a region, a city, or a district. Not many cities have adopted this approach on a full-scale, but a notable example is Anaheim, in California: the city council imposed

[8] *Gentrification*: "the process by which a place, especially part of a city, changes from being a poor area to a richer one, where people from a higher social class live". (From the Cambridge Dictionary).

a total ban in 2016 but withdraw the restrictions in 2019 after a wave of protests by STR and local shop owners, each lamenting economic losses for them and the city as a whole (Park, 2019).

Partial restrictions approach

This way of dealing with STRs is by far the most adopted and called out for by regulators. Partial restrictions are preferred over total prohibition because they allow cities to not lose the economic benefits of tourism while curbing its downsides. Partial restrictions can take many forms, the main being:

- Quantitative restrictions: they limit the number of STR listings in a city (for example through licenses), the number of visitors that can be hosted or the number of days a property can be rented throughout the year. This type of restriction has been adopted in London for example: properties can be short-term rented for a maximum of 90 nights per year.
- Qualitative restrictions: safety requirements and limitations concerning the type of property belong to this category.
- Locational restrictions: these are designed to delineate areas where STRs are allowed.
- Density restrictions: the number of STRs allowed varies depending on the neighbourhood and its characteristics (residential, commercial, etc.).

Most authorities, if not all, prefer to hold hosts responsible if rules are not obeyed. However, given the flexible and dynamic nature of these platforms, it is hard to precisely know whether hosts are complying with the laws and enforcement is not easy.

Lasseiz-faire approach

In reality, a *lasseiz-faire* approach should not be considered a regulatory approach at all, since no action is taken. However, deals between STR platforms and governments and city councils also fall in this category. In particular, many governments have struck deals with these platforms to collect taxes on every transaction, including tourism taxes that are to be paid at a more local level (Lines, 2015). For example, Airbnb has signed agreements with as many as 250 governments and administrations in 2016 alone (Benner, 2017), proving its interest in collaborating with the communities where it has a strong presence.

1.2.5 The future of Airbnb

Until now, Airbnb has been an extremely successful company that has managed to achieve exponential growth, widespread diffusion and which changed the way of travelling for thousands of people. The year 2020 was set to be a tipping point for the home-sharing industry, with the company going public on the American stock market and agreements to support events as important as the Olympic games that were planned to take place in Japan during the summer. Unfortunately, 2020 represented a turning point for the company on other fronts: the uncertainties, the travel bans and the fear of travelling brought by the global pandemic have upturned the situation. Nevertheless, the company managed to thrive and innovate in a hostile environment, ultimately going public in early December with a valuation exceeding $ 86 billion on its first day of trading.

Setting the most recent developments aside and avoiding to predict the evolution of such a particular situation, Airbnb's future still faces a number of challenges. The first of these has to do with the business travel segment, which the company struggled to penetrate but still wishes to successfully enter. In addition to this, the firm has plans to move beyond just accommodations in order to become a complete travel solutions provider, satisfying the needs of any customer for any type of trip. Experiences are a way of achieving this goal, but there still are considerable opportunities for development. The last important challenge concerns the relationship with regulators who are trying to rein in the digital economy and the negative externalities it is thought to generate.

The company is also carrying out various internal projects to innovate the travel experience, the furniture and the ambience of its listings. Behind one of these programs Samara[9], a product development team that is working on Backyard, "an initiative to prototype new ways that homes can be built and shared, guided by an ambition to realize more humanistic, future-oriented, and waste-conscious design" (Gebbia, 2018). Just like it has disrupted the accommodation industry developing home-sharing, Airbnb aims at designing and constructing homes that are to be sold to potential hosts and ordinary people. These homes are not going to be built solely from the perspective of sharing them one day, but also on the basis of environmental and social concerns. The idea is to use smart manufacturing techniques and technologies to create liveable dwellings that can be adapted and reconfigured over time, reducing the amount of waste as well.

1.3 The Italian Real Estate Market

This section aims at providing an overview of the Italian real estate market by looking at house prices, home ownership, and other indicators over time. Some characteristics will be measured against those of other European countries to provide a fair comparison. Data regarding the Italian real estate market is released every year through reports, databases, and analyses provided by OMI[10], a research center belonging to Agenzia delle Entrate, the Italian public agency responsible for tax collection and compliance. Other data sources include ISTAT, the Bank for International Settlements, the OECD and Eurostat. Data presented under the source name of OMI is drawn by its most recent report, which refers to 2019 (Festa, et al., 2020).

[9] https://samara.com

[10] OMI – Osservatorio del Mercato Immobiliare.

1.3.1 Market Description and Main Figures

Italian population at the end of 2019 was roughly 60,24 million, the third-largest in the European Union and the 23rd worldwide, albeit its size has been in steady decline since 2015. The number of families was estimated to be 26,19 million, with an average number of 2,29 components.

The total number of houses in Italy is approximately 31.208.161 according to the national 2011 census, 24.135.177 of which are either owner-occupied or rented out to people who reside in them. The remaining 7.072.984 are not, meaning that they may be empty houses, holiday homes, or occasional dwellings. To obtain and display insights on the Italian market it is necessary to use different data sources and to look at various indicators.

Records collected by OMI provide detailed data on residential real estate transactions for 7.603 municipalities (some are excluded due to different registry procedures); the value calculated for each municipality is defined NTN[11], which stands for "normalized number of transactions". The number of transactions has to be normalized because some purchases do not involve the sale of the entire property, therefore transactions are weighted taking into account the percentage of the property being sold or acquired. For example, if 50% of a property is sold, the relative NTN for the transaction will be 0,5 instead of 1. Figure *1.2* shows the evolution of NTN from 2011 to 2019, a period where the number of transactions hit a low in 2013 and took 5 years to reach a pre-2011 level.

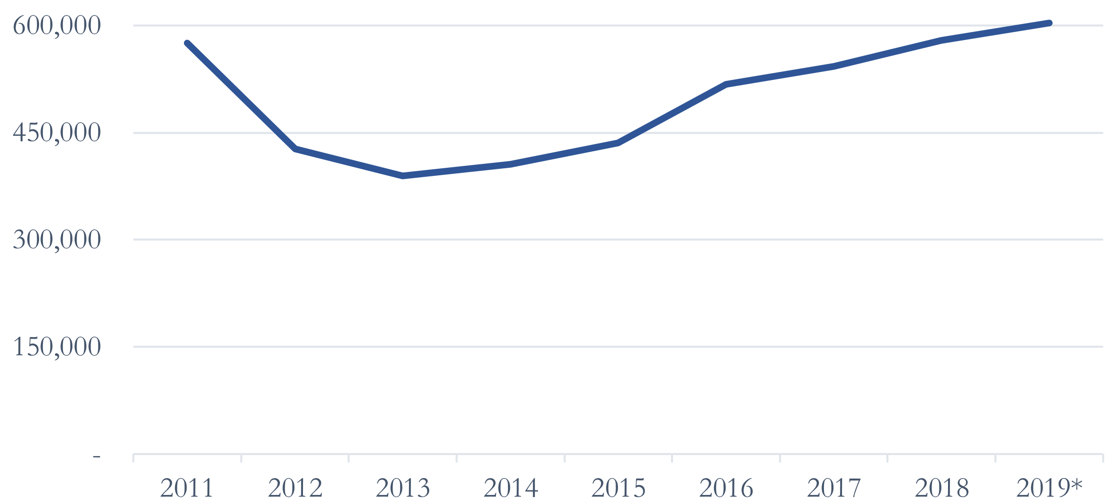

Figure 1.2. Yearly NTN for residential properties and buildings.
*Preliminary data. Source: OMI.

Although NTN is an important indicator, it is not enough to understand how active the market really is. To better achieve this, it is possible to look at an indicator named IMI[12], which

[11] NTN – *Numero Transazioni Normalizzate.*

[12] IMI – *Intensità del Mercato Immobiliare.*

stands for "real estate market intensity" and represents the percentage of residential real estate stock being sold every year; a higher IMI means a more dynamic market. In 2019 the average IMI for Italy has been 1,76% (up from 1,69% in 2018), meaning that out of 100 registered homes, 1,76 have been either sold or bought in the period. This indicator varies greatly and depends on factors such as the region or the municipality where the property is, with areas having an IMI as high as 5% and others where it hardly reaches 1%. Yet, even if they represent different measures, NTN and IMI have moved with a very similar trend over the years (Figure *1.3*).

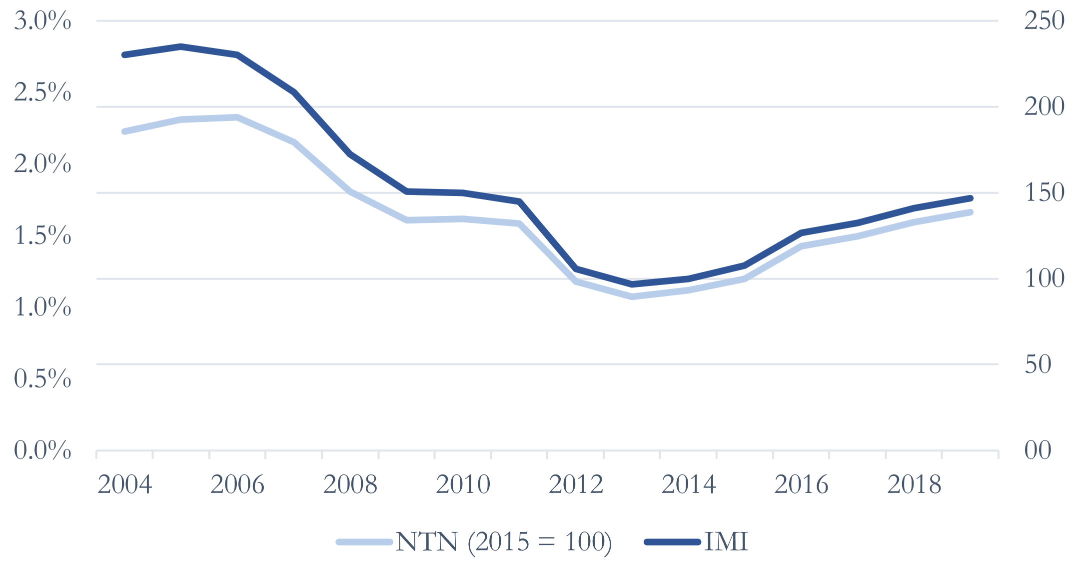

Figure 1.3. The evolution of IMI (left-hand scale) and NTN (right-had scale, 2015 = 100).
Source: OMI Annual Report 2020.

The average house bought in Italy in 2019 had a dimension of 106,2 m^2, about the same as in 2018 (105,9 m^2). Though, the most dynamic market segment, identified by its IMI, turned out to be the one for homes ranging from 50 to 85 square meters, which yielded an average IMI of 2,16% (Figure *1.4*).

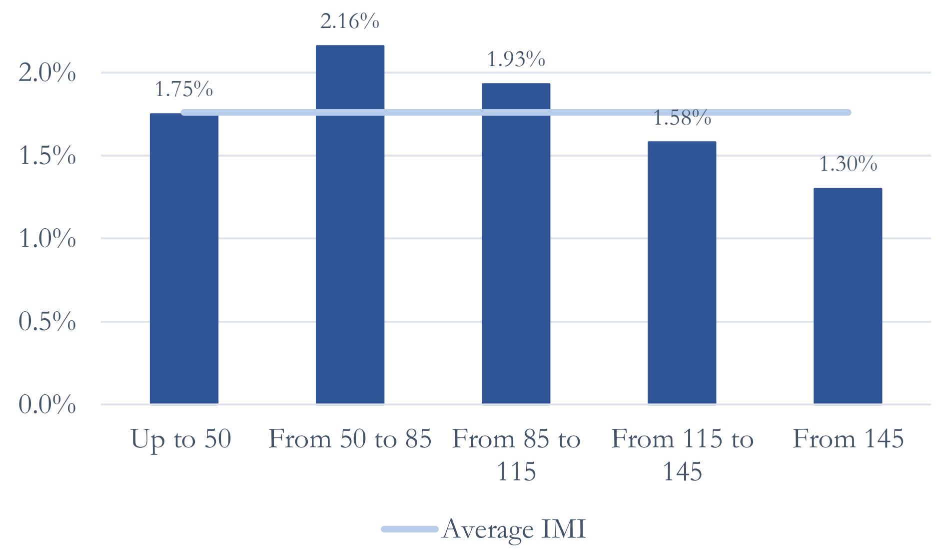

Figure 1.4. IMI values by market segment (identified by size in square meters) in 2019.
Source: OMI Annual Report 2020.

Financing of real estate transactions in Italy primarily relies on the issuance of mortgages, the provision of which changes over time: the willingness of banks to provide mortgages depends on factors such as the economic cycle, monetary policy and other financial and social aspects. Data collected by OMI for the year 2019 suggests that the number of normalized transactions that took place thanks to financing with the house being purchased used as a collateral were 286.474 (this indicator is named NTN IP), which corresponds to approximately 47,5% the total value of residential transactions (NTN). As Figure *1.5* shows, 2013 has once again been an awful year for the real estate market, with the lowest number of mortgages granted (regardless of considering them as a percentage of NTN or their absolute total value).

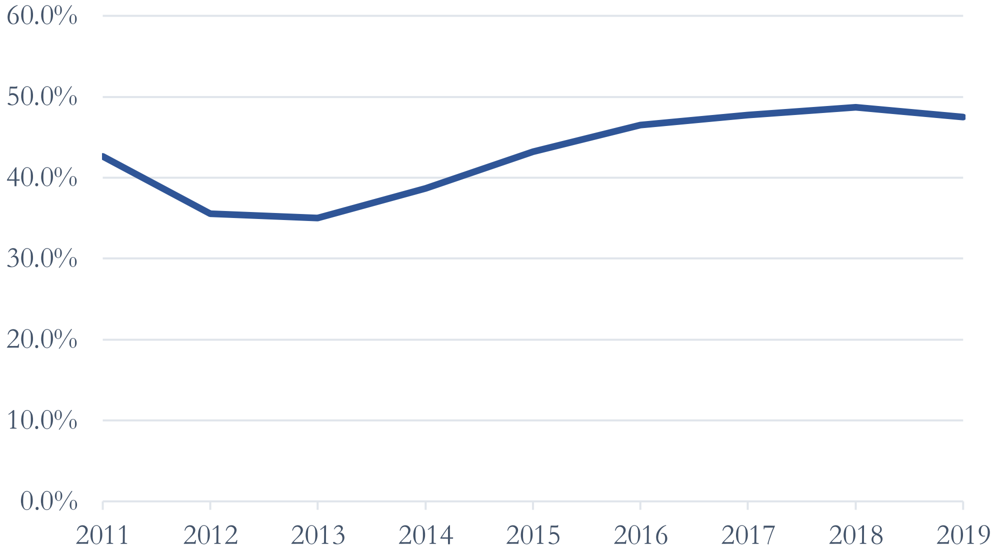

Figure 1.5. Share of mortgage-backed normalized transactions.
Source: OMI Annual Report 2020.

It is important to point out that mortgages supply is likely to affect house prices. Indeed, banks' looser lending policies provide the financial means necessary to buy a house to a wider population, which translates into a larger demand. For example, Mian & Sufi, (2008) have showed that ZIP codes with high shares of subprime borrowers experienced greater-than-average house price increases. A paper focusing on the Italian market for the period 2003-2015 presents evidence regarding how house prices respond to mortgage supply, indicating that a 10% increase in mortgages is estimated to cause a 1% increase in house prices (Barone, David, de Blasio, & Mocetti, 2020).

Despite this evidence, house prices, especially on the long term, depend on other demand and supply factors such as national income, land availability, demography, the labour market and the costs of construction. Yet, these elements could impact the number of transactions to a greater extent than prices. Indeed, residential real estate prices typically decline less steeply compared to other asset classes such as equities or commercial properties, while transaction volumes immediately drop. The reason why this happens is likely to stem from the behaviour of sellers, who forgo selling at a loss even if this means keeping a property for a considerable amount of time (Zhu, 2003). Figure *1.6* highlights this aspect for Italy, comparing the evolution of both residential property prices and their NTN. Clearly, house prices have had a shallower and less steep contraction over the years, while the normalized number of transactions more than halved between 2006 and 2013.

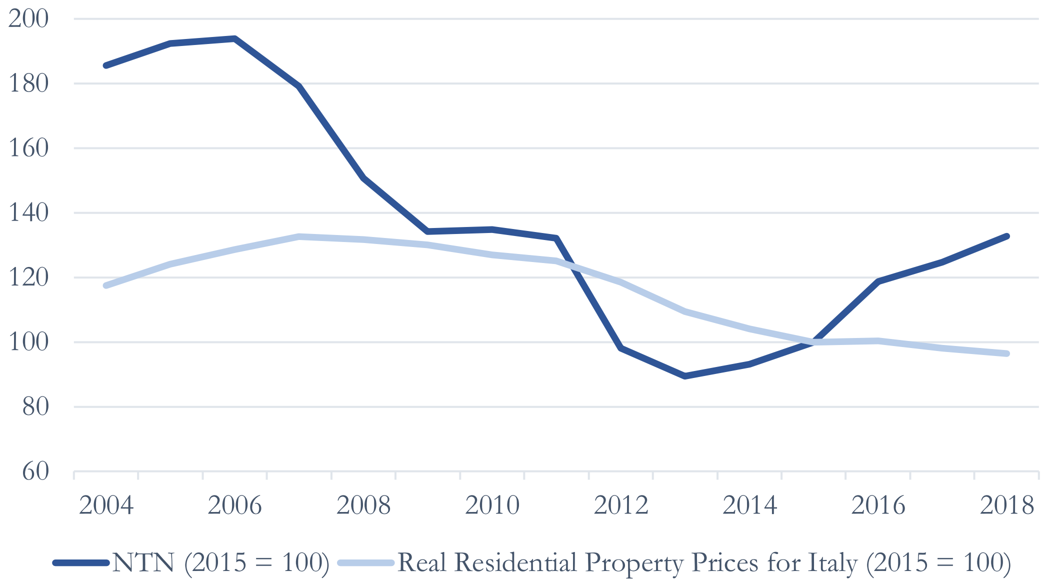

Figure 1.6. Evolution of NTN and property prices from 2004 to 2018 (2015 = 100).
Sources: OMI Annual Report 2020, Bank for International Settlements.

A final consideration to be made concerns the difference between the evolution of residential property prices for Italy and the rest of the Euro area. When the financial crisis struck in 2007, both indexes started to decline more or less equally (Figure *1.7*). However, prices for the Euro Area as a whole started picking up in 2015, while Italy's kept on decreasing.

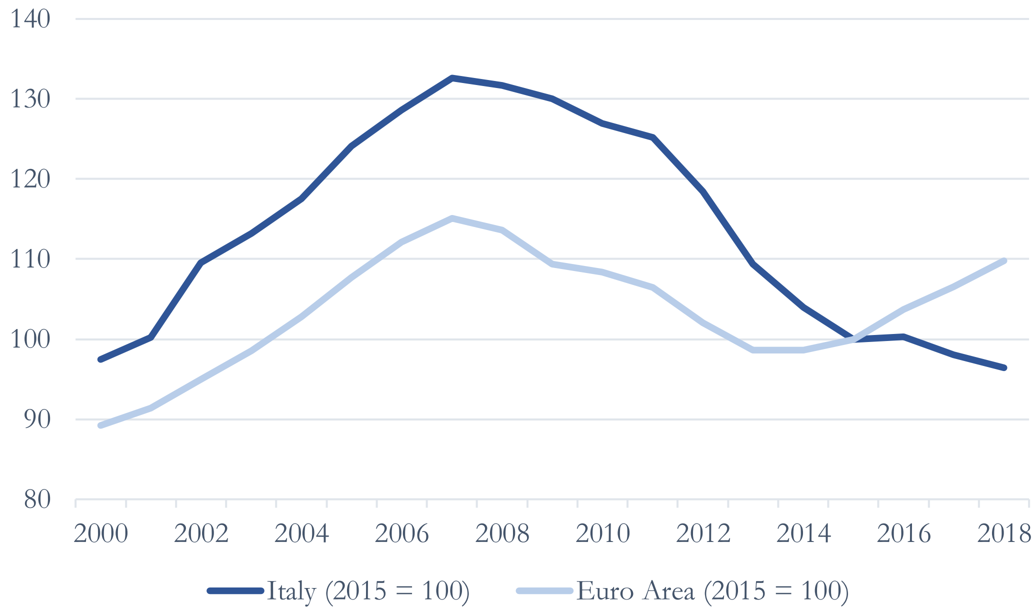

Figure 1.7. Real residential property prices for Italy and the Euro Area (2015 = 100).
Source: Bank for International Settlements; retrieved from FRED.

1.3.2 Owning vs Renting

Italian home ownership rates from 2004 to 2018 have not changed significantly. In fact, the share of the population living in owner-occupied dwellings has only swung between 72,3% and 74,2% in the period. However, by dividing households into separate income groups, above and below 60% median income, it is possible to see how the percentage of households belonging to the second income bracket who live in owner-occupied homes is significantly lower. Moreover, the share of lower-income families not resorting to renting a home has declined from more than 58% to almost 52%, while the same figure for those above the median income threshold has remained approximately the same.

Nonetheless, the average ownership rate in Italy is now significantly higher than 50 years ago, when it averaged 60% (Chiri, Borselli, Buoncompagni, & Manestra, 2013), but why has it become so high? High agency and transaction costs refrain owners from selling their homes, hindering geographical mobility, and life choices when socio-economic transitions are in place. Additionally, the tax system has been designed in a way that it is an incentive to own a home rather than renting one, given the low tax rates that apply for home-ownership compared to the higher rates to which rental incomes are subject to.

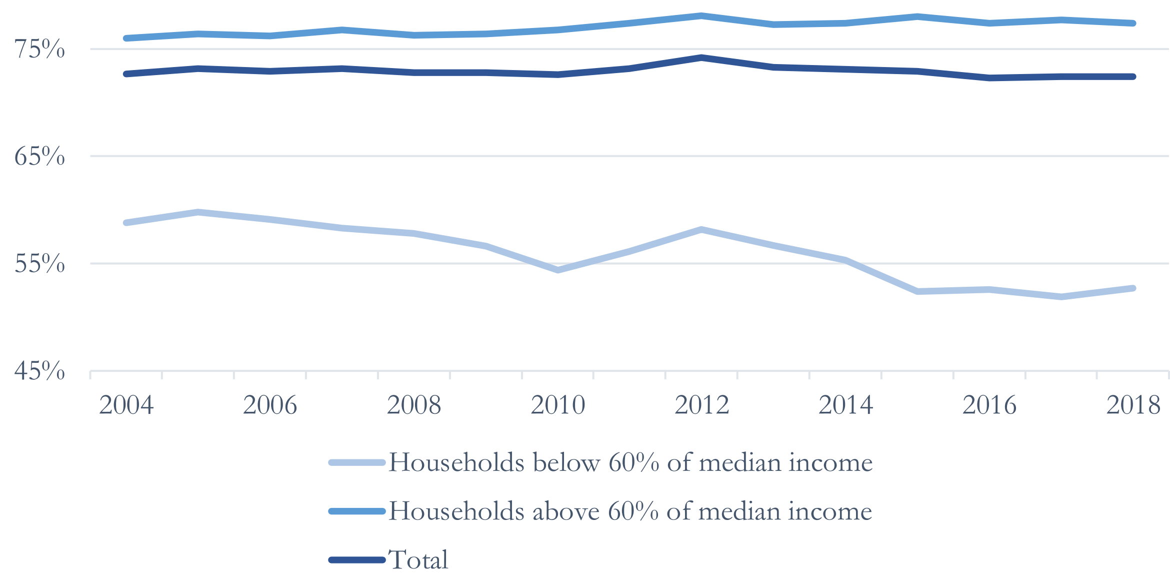

Figure 1.8. Share of households living in owner-occupied dwellings by income group, Italy.
Source: Eurostat, 2018.

Comparing the Italian context with that of similar European countries, only Spain has a higher percentage of owner-occupiers, while Germany has a profoundly different structure, with almost half of the population resorting to renting (Figure *1.9*).

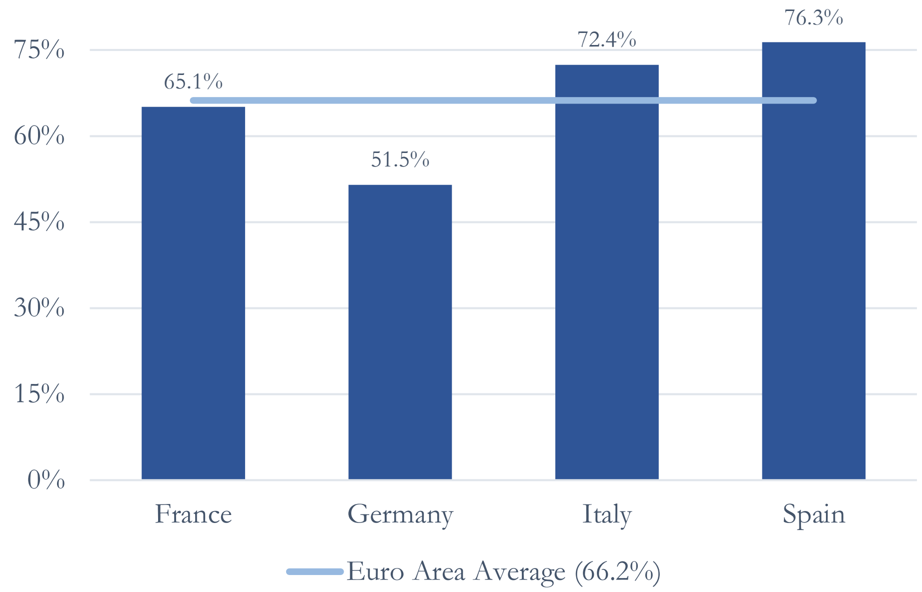

Figure 1.9. Share of households living in owner-occupied dwellings in selected European countries. Source: Eurostat, 2018.

Despite these differences, by observing data in more detail it is evident that most European countries present a common characteristic: poorer families resort to renting more frequently than those belonging to higher income groups. In Italy the situation has changed over time: as Chiri, Borselli, Buoncompagni, & Manestra (2013) point out, in the 1970s the distribution of households not living in owner-occupied dwellings was uniform among the different income groups, while it is now skewed towards the less well-off.

Considering data back to 2000, the cost of renting a home in Italy has closely followed the level of inflation: the lines plotting the two indicators overlap one another most of the years. On the other hand, real residential property prices have experienced a period of inflation during the years from 2001 to 2007, after which they started decreasing constantly, plummeting below the level registered at the beginning of this time-series (Figure *1.10*).

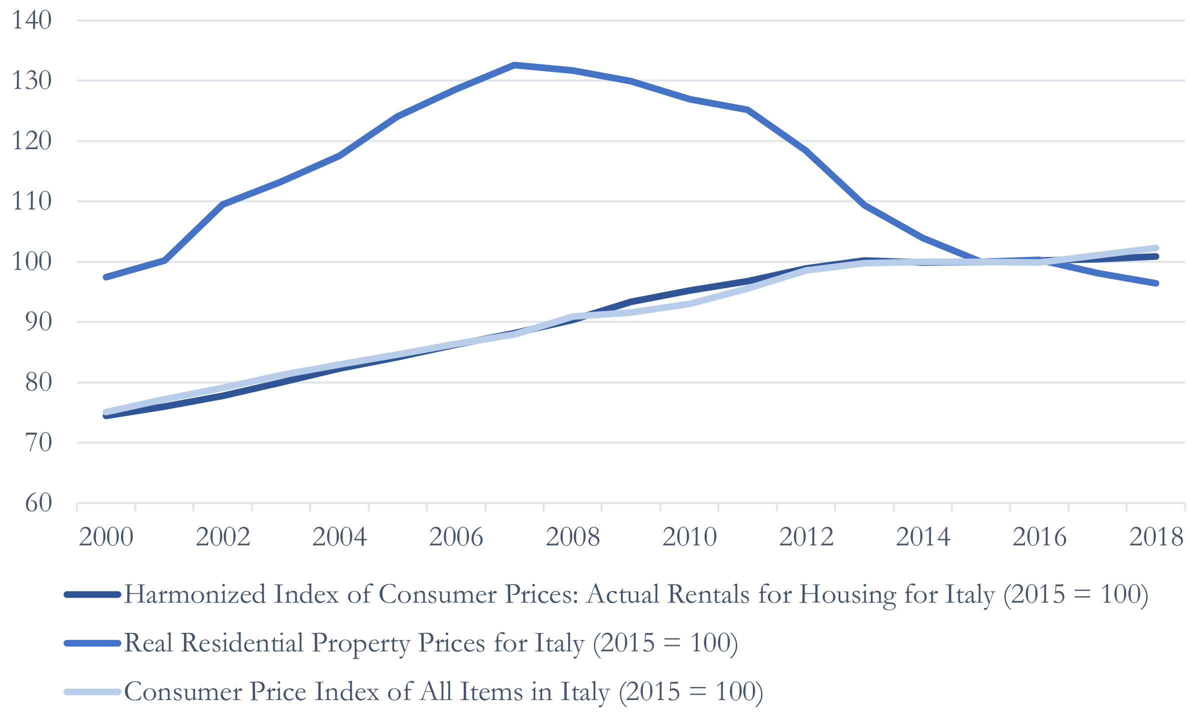

Figure 1.10.
Source: Bank for International Settlements, Eurostat, OECD; retrieved from FRED.

1.4 Italian Regulation on Rents

1.4.1 Long-Term Rents

The different types of long-term residential lease agreements in Italy mainly differ by two characteristics: the rental paid by the tenant and the length of the contract. Landlords can decide between *contratti a canone libero*, where the rental rate is freely set by the owner of the property, or *contratti a canone concordato*, for which minimum and maximum rates apply. These rates vary at the local level, depending on the region, city or the type of home considered. Furthermore, contracts differ for their duration, with temporary contracts lasting from a minimum of 1 month to a maximum of 36 months, while non-temporary contracts start from a minimum duration of 36 months. The main contract types are the following:

- *Uso transitorio*: the contract has a minimum duration of 1 month and a maximum of 18 months, with a fee that in some cases has to meet local guidelines. This contract cannot be used for tourism reasons.
- *Uso transitorio per studenti universitari*: a particular type of temporary contract aimed at university students; the minimum duration is 6 months and it expires in 3 years. Rental rates are freely set unless local laws impose limitations.
- *Canone concordato*: the rental rate is subject to limitations set by the municipality or other local authorities; the contract starts with a 3-years duration and is automatically renewed for another 2 years (3+2).

- *Canone libero*: no constraints on the rental rate and a minimum duration of 4 years that can be automatically renewed for another 4 years (thus known as the "4+4").

Using data provided in the last report released by OMI (Festa, et al., 2020), it is possible to break down the distribution of rental contracts arranged in 2019 (Figure 1.11). Unsurprisingly, more than 75% of contracts have been non-temporary, with two-thirds of these being *a canone libero*.

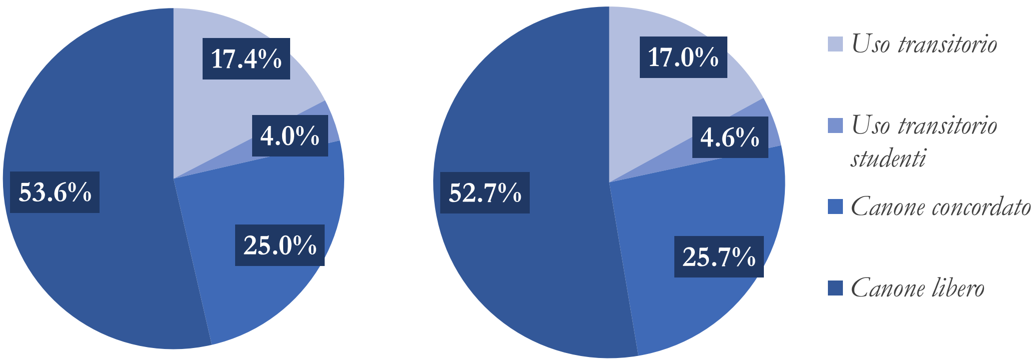

Figure 1.11. Number of contracts (left) and total amount of rents (right) by contract type.
Source: OMI Annual Report 2020.

Italian laws require rentals to be registered if their length exceeds 30 days. Once a contract for residential purposes is registered, the landlord can decide the what type of tax scheme to adopt. The two schemes to choose from are:

- *Regime ordinario*: the IRPEF[13] rate (which varies depending on the landlord's income bracket) is applied.
- *Regime sostitutivo*: a specific flat tax (also known as "*cedolare secca*") is charged depending on the type of rental agreement: 21% for a *canone libero* contract and 10% if it is a *canone concordato*. Additionally, some registration fees are no longer due.

1.4.2 Short-Term Rents

Legislation concerning short-term rentals has been updated in 2017 with the decree n. 50/2017. Since then, rental agreements lasting no more than 30 days can be subject to the 21% flat tax regime (*cedolare secca*) as well as the ordinary IRPEF rate. These agreements do not need to be formally registered, can include the offering of ancillary services such as an internet connection or a cleaning service, but cannot involve other services that may be classified as commercial activities, such as the provision of food. There is no limitation regarding the maximum number of days a home can be rented with a short-term agreement over a year (as is the case in some cities in other countries). Moreover, the law states that the agreement is effective even when the counterparts do not directly engage with one another (which is what happens on platforms like

[13] IRPEF is the progressive income tax applicable to individuals in Italy.

Airbnb), and this is the reason why online agents and intermediaries are explicitly required to keep a record of such contracts. In the event that they also take part in the transaction, online agents are required to collect the 21% flat tax.

The Italian parliament has recently started discussing a possible reform concerning both the fiscal regime and other limitations that should apply to short-term rents. These questions have been raised, among others, by the mayors of some cities (the mayor of Bologna has been on the front line) believed to withstand the negative effects of this phenomenon. Proposals currently include three different approaches: the possibility for cities to introduce licenses to limit the number of housing units available for vacation rentals, the obligation for those who rent more than 3 properties to constitute a commercial activity, and the removal of the 21% flat tax in favour of the IRPEF rate (which is higher) in the event of more than 3 properties.

Chapter 2

Literature Review

The previous chapter described the sharing economy, the business model of one of its most relevant players, and its impact on the hotel industry, which is seemingly the most affected by its presence. This chapter instead concentrates on the analysis of the most relevant works aimed at studying the impact of Airbnb on the real estate market, considering its influence on both home and rent prices.

2.1 Research Conducted on American Cities

The first researches that have been conducted to investigate the effect of Airbnb on the housing market involved American cities. The reason for this is that Airbnb was born in the United States and it is in this country that it grew very rapidly at the beginning.

One of the first cities to be analysed was Boston, which is at the centre of Horn & Merante's (2017) study. The authors investigate whether asking rents in the city have risen as a consequence of Airbnb diffusion and whether these rent increases, which have annually averaged 5% in the years prior to the analysis, have been caused by a tightening in supply. Airbnb listings in the city have grown 24% from 2015 to 2016 with 82% of hosts listing only one property on the website. However, the properties belonging to the remaining hosts (18%) amounted to 46% of the total. Data available to the authors allows the use of a fixed effects model to control for unobserved variables at a neighbourhood-specific level. Doing so, their hedonic regression takes into account characteristics such as crime rates, the number of building permits and new restaurant openings. An interesting metric created by the authors, which is also going to be used in Chapter 3 for this work, is a sort of 'Airbnb density', a measure used to differentiate neighbourhoods on the basis of characteristics such as their population and housing market. The neighbourhoods with the highest densities were found to have up to 5% of the housing stock listed on Airbnb.

Another early research on Airbnb was conducted by Sheppard & Udell (2016) on the city of New York, which has a highly regulated housing market. The authors aimed at answering the following question: "*What is the impact of being able to transform residential properties into revenue streams and partly commercial residences?*". Sheppard & Udell expect Airbnb to have an impact on property values as well as rental prices for the same reasons that have already been pointed out previously: an increase in willingness to pay and additional income opportunities. Also, property values might fall due to Airbnb listings in the event that negative externalities caused by guests have a negative impact on the perception of the neighbourhood, but results show this is not the case.

Two different approaches have been used to determine the impact of Airbnb on house prices. First, a traditional hedonic approach has been set up with sales data covering the period from 2003 to 2015; the results suggest that a doubling of Airbnb listings increases house prices between 6% and 11%. The difference-in-differences approach has instead been used considering a treatment period starting from 2010, which is when the number of Airbnb listings in the city started to be considerable. The estimated impact found with this technique is much higher, since properties subject to the Airbnb treatment experienced a 31% surge in value.

In a completely different work by scope, Barron, Kung, & Proserpio (2017) have conducted a nation-wide empirical study to investigate the relationship between housing affordability and the development of the sharing economy. By studying the effect of home-sharing on the long-term rental market between 2012 and 2016, the authors find that a 10% increase in Airbnb listings leads to a 0,42% increase in rents and a 0.76% increase in house prices, with a larger effect in neighbourhoods where the share of owner-occupiers is smaller, indicating that absentee landlords have been switching the destination of their homes from the long-term to the short-term market. To control for unobserved zipcode-specific time-varying factors, the authors use an exogenous instrumental variable that is built using the interaction between Google search trends and a zipcode-specific *touristy* measure referring to the year 2010. This measure is derived by the number of restaurants, hotels and other potentially attractive establishments for tourists, meaning that a higher number of them is expected to lead to an interest for local landlords to relocate their properties on the short-term rental market.

Similarly to what Horn & Merante did, the model that has been used takes into account fixed effects that are specific for the year and the zipcode considered. The difference in this case is the focus on owner-occupiers, which are essentially people who live in their own house, opposed to the rest who are tenants, thus people living in someone else's property. Regression results show that a higher owner-occupancy rate is associated with a lower effect of Airbnb on both rental rates and house prices. Also, Barron, Kung, & Proserpio provide evidence that absentee landlords are reallocating their properties from the long-term market towards short-term accomdations.

To complete the overview of literature on American cities, it is worth mentioning the work by Koster, van Ommeren, & Volkhausen (2019) regarding the effect of a regulation aimed at reducing the number of Airbnb listings in some cities in the county of Los Angeles. Specifically, out of the 88 cities belonging to the county, 18 have implemented regulations to limit the spread of home-sharing. Since restrictions do not apply to all cities, the authors are able to use a spatial regression combined with a difference-in-differences approach to capture the effects of Airbnb on the real estate market. In the county of Los Angeles 2,5% of residential properties are listed on Airbnb, with 60% of them being entire properties. However, the 2,5% figure is an average and has little significance; therefore, to capture Airbnb demand area by area, the authors used the so-called *Airbnb listings rate*, which they found dividing the number of listings by the number of housing units for each area of interest.

Using Airbnb data from 2014 to 2018, they find that the effect of introducing the new regulations is significative, with house prices decreasing by approximately 3% across the cities; a similar figure is found for rents as well. However, areas with high listings rates have experimented sharper price variations, up to 30%. The finding is in line with the authors' prediction that Airbnb listings are not randomly allocated and that tenants living in areas that are popular among tourists are the most susceptible to price increases. The regulation is thus regarded as useful from the tenants' perspective, because it cools down, and even reverses, the upward pressure on rents in those areas where landlords can easily relocate their home on the short-term market.

2.2 Research Conducted on European Cities

Researches focusing on European cities are more recent and interest only some of the main destinations in the continent. Indeed, there is a lack of papers focusing on some of the most important cities by number of arrivals, among which is Rome for example.

Two important researches have been conducted on the Spanish city of Barcelona. The first (Segù, 2018) was aimed at assessing the impact of Airbnb's market entry in the city using data from Idealista, the online real estate portal, and InsideAirbnb. As already disclosed for other cities, multi-property hosts are very active in Barcelona too, with 61% of listing belonging to this type of owners. The average number of properties belonging to a host was found to be 1,82, but the top 1% of hosts owned a staggering 15% of listed properties in 2015. In order to assess the impact of Airbnb on rents, it is necessary to handle endogeneity issues related to the location of listings, which are likely to influence both the number of listings and price variations for rents. To deal with endogeneity, the author uses a Bartik-like instrumental strategy which takes into account both time and space variations by considering the distance from the beach and the total number of tourists arriving in the city.

The empirical strategy is thus focused on the distinction of listings on the basis of their distance from the beach, which is said to be disdained by residents but appreciated by tourists. In addition, controls for gentrification processes are included in the analysis, given that these processes may have had an impact on rents as well, regardless the rise of home-sharing platforms. By taking these features into account, the results show that the platform is responsible for a 4,1%-5,8% increase in rents between 2009 and 2016, depending on the specification used.

An updated, more detailed and slightly different version of the previous work has been published by Garcia-Lopez, Jofre-Monseny, Martinez Mazza, & Segù (2019). Using different data sources, the authors still find that commercial listings make up a significant share of supply in the city Barcelona: more than 75% throughout the years taken into account. Moreover, Airbnb listings relative to the number of rented units in the city were 6,84% in 2015, while approximately 2,06% of all residential properties were listed on Airbnb. Since the average long-term rental is 735€ per month – thus 11€ per night – and the average price for on Airbnb is 71€ per night, home-owners can manage to earn the same money by renting their property on the short-term market for only 10 days a month. The authors' concern is that neighbourhoods where Airbnb has grown the most are the ones most susceptible to gentrification processes, which in turn may have been sharpened by this type of economic considerations by landlords.

To avoid confounding effects in the analysis, controls for time-varying neighbourhood demographic characteristics are applied, Google trends are used to track Airbnb activity over time, and proxies regarding tourist appeal (mainly considering the proximity of landmarks and monuments) are included. By doing so, the model is able to predict where Airbnb properties are more likely to be located and when listings are more likely to appear. Depending on the number of active listings, neighbourhoods are also classified into two categories, with *high Airbnb areas* corresponding to the top 10% of neighbourhoods (ordered by this metric), in which approximately 5% of all housing units are listed on the platform. These areas present higher property and rent prices compared to the rest, with a gap that has widened even more in the last years considered in the study (the authors set 2012 as the pre-Airbnb year and use 2016 as the last one in the analysis). The resulting model predicts that Airbnb increases both housing prices and rents, with a heavier effect on the former. Also, as the following table shows, the effect of Airbnb only explains a small portion of the increase in rents and prices for *average neighbourhoods*, but the effect in *high Airbnb areas* is greater.

	Average Neighbourhood	**High Airbnb Area**
Rents	+1,9 %	+7 %
Posted Prices	+3,7 %	+14 %
Transaction Prices	+5,3 %	+19 %

As a last remark, the authors show that Airbnb listings reduce the number of residents in a specific area, primarily through the reduction of long-term tenants and because of reduced affordability.

Ayouba, Breuillé, Grivault, & Le Gallo (2019) also published an article addressing rent affordability, evaluating whether Airbnb rentals affect rent prices in eight different French cities. Listings data was taken from AirDNA and covers the period of 2014-2015, while rental market data was provided by a network of observatories. The analysis is based on a hedonic model working on spatio-temporal data which is estimated through the OLS method. Of course, rent prices reflect socio-economic conditions, so a number of factors and characteristics are taken into account; for instance, hotel density is found to have an impact on rents for the cities of Paris and Montpellier. Moreover, entire home rentals are divided into 'professional' and 'nonprofessional' depending on the number of days they are listed on the platform, using the 120-days threshold imposed by the government. Thus, a listing that is online for more than 120 days is considered 'professional', but the same also applies to entire home listings belonging to hosts advertising more than one property.

An Airbnb density metric obtained by dividing the total number of listings by the housing stock in a certain area was used for the purpose of this paper as well. Taking it into account, an increase in listings is found to have an impact on rents in three cities. However, restricting the focus on professional rentals only, the results remain significant for just one of the cities. On the other hand, considering only new rental contracts, the impact of Airbnb is even higher, suggesting that owners are well aware of the alternatives to a long-term agreement. Albeit Barron, Kung, & Proserpio found that a higher share of owner-occupiers leads to a weaker impact of Airbnb, the same in not true for the French cities, since the share of owner-occupiers leads to mixed results. Indeed, in Paris the results are even counterintuitive, with the impact of Airbnb increasing along with the share of owner-occupiers.

Overall, the study establishes that the density of Airbnb listings leads to an increase in rents in three out of the eight cities and, taking into account those listings defined as 'professional' Airbnb listings, the effect becomes greater, but only for some of the cities. Hence, the final conclusion by the authors is that Airbnb presence does not necessarily lead to rent increases, with the exception of Paris which is the only city always affected, regardless of the variables considered.

The last study worth mentioning was carried out by Duso, Michelsen, Schafer, & Tran (2019) and is closely related to the work by Koster, van Ommeren, & Volkhausen on the county of Los Angeles following the introduction of restrictions for short-term rentals. In this case the focus is Berlin, where a law aimed at preventing the excessive use of properties for short-term services acts as an exogenous variation in Airbnb listings, from which it is possible to infer their impact on rents. The authors focus on entire homes, since on one hand they are the ones targeted by the new law (ZwVbG) that came into effect on May 1, 2014 and, on the other hand, they are the most relevant for determining the impact on the housing market. The regulation included a two-year transition period for apartments that were already used for holiday leases, on the condition that owners register their activity with the authorities. At the end of this period, the number of Airbnb listings, particularly entire homes, in Berlin dropped. In order to estimate the causal impact of Airbnb on rents, it is necessary to avoid the potential endogeneity caused by omitted variable bias and reversed causality. To do so, the authors consider ZwVbG as having no impact on rent prices but only on Airbnb availability, and introduce a set of control variables to take into account exogenous factors.

Data sources include Airbnb listings data, rents, but also information on the characteristics of the neighbourhoods: number of restaurants or supermarkets, the age of buildings, location of bus stops and other metrics that are able to differentiate neighbourhoods. The results show that an additional Airbnb listing within 250-meters from a housing unit leads to a rent increase of 0,067 € per square meter a month which, considering the average rent, amounts to approximately a 0,7% increase.

The conclusions brought by these researches, even if not always as robust as the expectations underlying the work, clearly show how the influence of Airbnb is widespread and affects different cities in similar ways. These findings provide a solid ground for exploring the same issues in the Italian landscape and serve as a benchmark for interpreting the results. Moreover, this research will benefit from the adoption and inspiration provided by the technical arrangements and methods that have been put in place at some stages of the aforementioned analyses.

Chapter 3

Analysis of Data from Airbnb, OMI and Idealista

3.1 Data Sources

To explore and analyse the impact of Airbnb on the real estate market, three different data sources have been used. The most important dataset has been provided by AirDNA, which is a company providing insights and details regarding Airbnb listings. Real estate market data has been taken by OMI (the same source already used in 1.3) and Idealista, an online real estate portal.

3.1.1 AirDNA

Data provided by AirDNA has been collected through *web scraping*, a technique where a software automatically records information found on a website. AirDNA does this at specific time intervals for listings in some cities, gathering all the information in databases. Data is available on a quarterly basis for the period spanning from the last quarter of 2014 to the last quarter of 2019.

The data provided contains many variables, some of which are not useful for the purpose of this work. What follows is a list of the most important variables that have been used for the analysis:

- `PropertyID`: it is the unique id assigned by AirDNA for each vacation rental listing;
- `YearQuarter`: the period to which the values refer to;
- `OccupancyRate`: calculated as $\frac{Total\ Booked\ Days}{Total\ Booked\ Days + Total\ Available\ Days}$ for vacation rentals with at least one booked night;
- `Revenue`: total revenue earned in the period, including both the advertised price of the booking and the cleaning fees;
- `NumberOfReservations`: number of unique reservations during the period;

- `ReservationDays`: total number of listing calendar days that were classified as reserved during the reporting period (each calendar day is classified as either A=available, B=blocked, or R=reserved);
- `AvailableDays`: total number of listing calendar days that were classified as available during the reporting period.
- `BlockedDays`: total number of listing calendar days that were classified as blocked during the reporting period.
- `CityAirDNA`: the city where the property is located;
- `Latitude & Longitude`: the property's geographical coordinates;
- `Active`: vacation rentals that had at least one calendar day classified as reserved during the reporting period;
- `PropertyType`: it is the type of accommodation (Flat, Villa, Studio, Cottage, etc.);
- `ListingType`: a listing can either be an Entire Home, a Private Room, a Shared Room, or a Hotel Room;
- `PublishedNightlyRate`: default nightly rate for the rental;
- `AirbnbPropertyID`: it is the unique Airbnb property ID;
- `AirbnbHostID`: it is the unique Airbnb host ID.

This database has been merged with data from Idealista, assigning each listing to a specific neighbourhood on the basis of its coordinates. The introduction of a common element between the two datasets allows for aggregate measures to be calculated in 3.3 and facilitates the econometric analysis in Chapter 4.

3.1.2 OMI

Data collected by OMI are aggregated on the basis of geographical areas named *Zone OMI*, which have different dimensions and are typically homogeneous in characteristics. Each area is identified by a unique code starting with the letter referring to the category it belongs to. The categories identify 5 different area groups:

- B – Central areas
- C – Semi-central areas
- D – Areas on the outskirts of cities
- E – Suburban areas
- R – Exurban areas

Properties are subject to grouping as well, since they are distinguished in residential properties, commercial properties, warehouses and others. For the purpose of this work, only residential properties have been considered; these belong to the 'A' category, which is divided into 11 different properties types, from code A01 to code A11. The A10 category refers to offices and has thus been discarded from the analysis.

The first type of data used for the analysis describes the stock of properties and housing units found in each of the OMI areas in the years 2016, 2017 and 2018. Data is available for any of the different property categories, but only values relative to the 'A' category have been used. The data set includes the following variables:

- Year;
- City;
- OMI area;
- Property type among each category.

The second type of data provided by OMI has to do with prices. For both sales and rentals, the dataset provides the maximum and the minimum amount registered in the period. Assuming these prices are evenly distributed, an average value has been calculated for every data point. The main variables are the following:

- City;
- OMI area;
- Property type description;
- Conservation state: it can either be (on a descending scale) *ottimo*, *normale*, *scadente*;
- Minimum and maximum selling price (€/m^2);
- Minimum and maximum monthly rent price (€/m^2).

It is worth mentioning that price values obtained through this dataset are not necessarily accurate. Since the data provided by OMI is the same collected by Agenzia delle Entrate to determine tax payments, there is an incentive for property owners to under report incomes from rentals or transaction values for property purchases to avoid or reduce their tax liabilities. The extent of the phenomenon is difficult to assess so data cannot be adjusted, but it is important to be aware of the distortion.

3.1.3 Idealista

Other real estate data have been provided by Idealista, an online real estate portal and property website used by property owners and real estate agencies to list properties to either sell or rent. The frequency of data is quarterly, starting from Q1 2012 until Q1 2020 and only average prices are provided. Every city is divided in different neighbourhoods, defined by Idealista, which correspond to areas supposedly homogeneous in characteristics such as the type of buildings, their distance from the city centre and similar parameters. For example, the city of Turin has been divided in 27 neighbourhoods, whereas Milan in 79.

The data provided refer to both rental and selling prices in euros per square meter but, differently from the dataset provided by OMI, the values collected by Idealista are expected to be slightly higher than the actual amount paid at the transaction. Indeed, people may tend to request higher prices to allow a margin for negotiation, because they do not know the market too well, or because the price the buyer (or tenant) is willing to pay is simply lower and the seller (or landlord) ends up accepting it for a lack of demand. Therefore, it is impossible to determine the amount actually paid by the counterpart, but over time the general trend is likely to reflect the real evolution of transaction prices.

As previously mentioned, Idealista and AirDNA datasets have been merged to create a single database where Airbnb data is linked to real estate data by matching a listing's location to an Idealista neighbourhood, identified by the variable `NeighbourhoodIdealista`.

3.1.4 Combining Idealista and OMI Datasets

The values in both the datasets are expected to present a distortion, so it would be interesting to merge the two datasets and see whether the trends reported are the same across the two sets of data. What complicates this process is the fact that both datasets report data for geographical areas that mostly do not correspond and have very different sizes. Indeed, OMI areas present strongly variable dimensions, with areas located in the city-entre much smaller than the ones in the outskirts. As Figure *3.1* shows, however, Idealista areas (outlined in red) are more homogeneous.

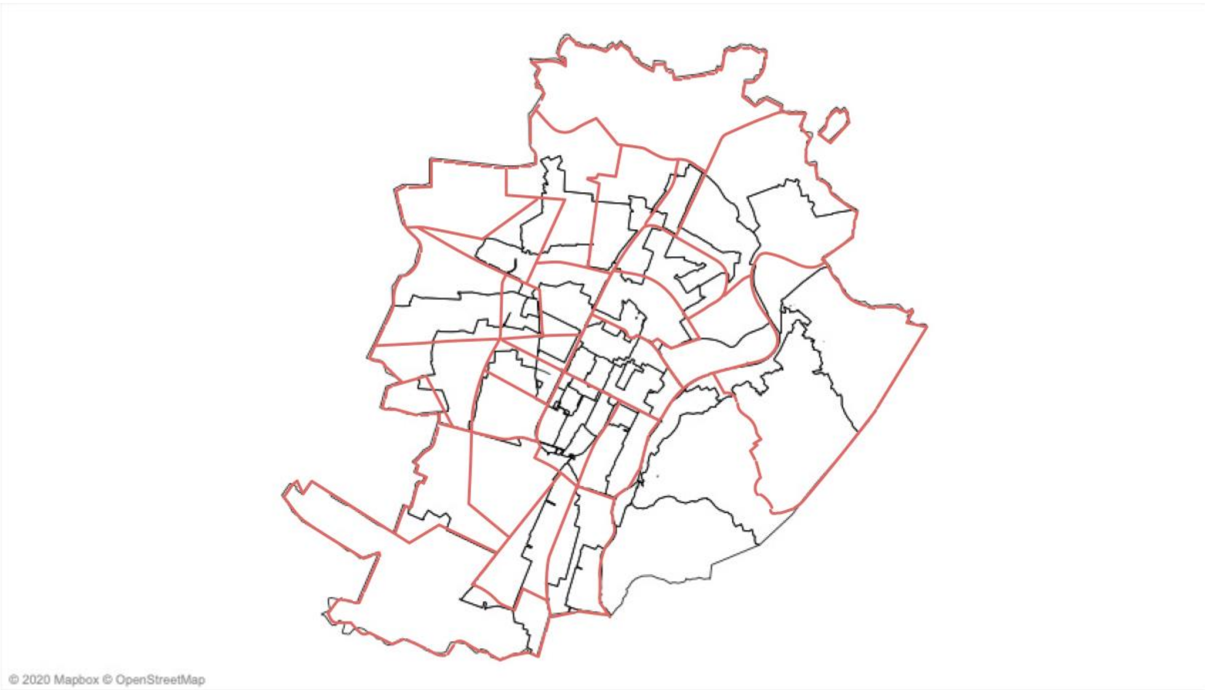

Figure 3.1. Idealista neighbourhoods (red boundaries) and *Zone OMI* (black boundaries) compared.

To establish a relationship between these values, a geographical confrontation is needed. Since the areas are uneven, many of them do not have boundaries in common, and they often overlap, an approximate solution was found to tackle the problem. The first assumption is that any given OMI is uniform in its characteristics, meaning that the number of residential buildings, and also the number of properties sold or rented in a certain period, is evenly distributed across the district. This means that if a certain area – imagine a 100x100 m^2 square – has 100 housing units, these are not concentrated in specific part of the square, there will rather be a housing unit once every 10 meters.

Using Google Earth, it is possible to import the coordinates defining the boundaries of the neighbourhoods defined by both Idealista and OMI and measure their extension (in either m^2 or km^2) Importing the boundaries from Idealista and overlapping them with OMI's, it is possible to measure the percentage of an OMI area belonging to an Idealista area by calculating a ratio where the denominator is the total extension of a specific zone and the numerator is the area part of an Idealista neighbourhood. The formula:

$$\%\ of\ OMI\ area\ part\ of\ Idealista\ area\ Y = \frac{OMI\ area\ overlapping\ Idealista\ area\ Y\ (in\ km^2)}{Total\ OMI\ area\ (in\ km^2)}$$

These values can be used to populate a matrix where the rows represent OMI areas while the columns report the 27 neighbourhoods defined by Idealista. The numbers in each cell report what percentage of a specific OMI area (on the row) is included in any of the Idealista neighbourhoods (on the columns). For example, Table 1 shows that 77% of OMI area B4 is part of Idealista neighbourhood *Centro Storico*, while the remaining 23% belongs to *Crocetta*. It is important that each row's total is 1, otherwise some data will be lost.

	Centro Storico	San Salvario	Crocetta
B1	1	0	0
B2	1	0	0
B3	1	0	0
B4	0,77	0	0,23
B5	1	0	0

Table 1. Focus on how the OMI/Idealista matrix was populated.

The whole matrix can be found in Exhibit 2, whereas its use will be described in the following sections.

3.2 OMI Analysis

This section describes the main attributes regarding residential real estate in the city of Turin, mainly considering the stock of properties composition.

3.2.1 The Housing Units

OMI provides data on the city of Turin dividing it into 41 different sections. The heat map in Figure *3.2* shows the number of housing units in each of these sections, which tend to have fewer units when they are central or refer to the hillside. The map has been obtained by extracting the number of properties belonging to the 'A' category in 2018, with the exception of A10 properties which are offices.

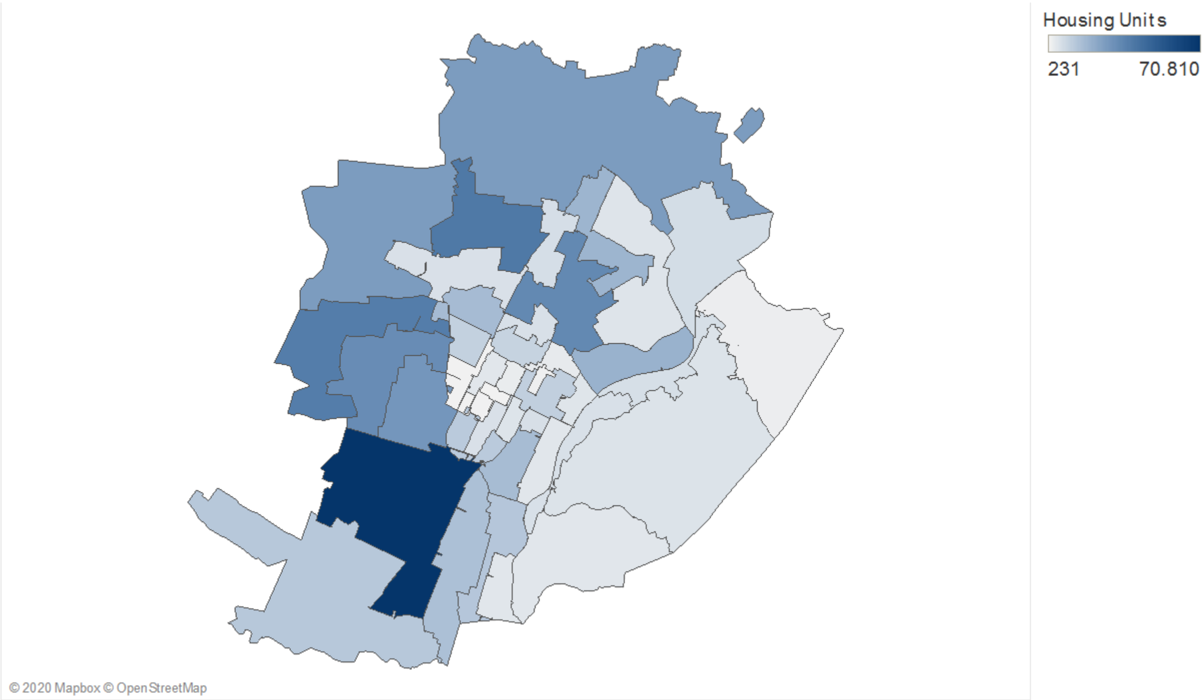

Figure 3.2. Housing units by OMI area in the city of Turin.
Source: OMI, 2018.

Figure *3.3* presents the precise number of housing units for each of the 41 areas, which totalled 498.215 in 2018. These numbers are extremely different across neighbourhoods, since OMI areas span from very small central zones to vaster ones such as D5 or D8. The graph includes data from three different years only to show that the differences between them are very small. To have a clearer representation, Figure *3.4* shows the variation in total number of housing units registered in 2016 and 2017 relative to the estimated stock in 2018. The differences are negligible, except for some small areas (such as B1 or B3) where there have been larger changes due to the relatively lower stock, meaning for example that a large commercial building that was converted into residential units is immediately impacting the local stock. Because of these considerations, from now stock data will only refer to the year 2018 and it will be assumed that the distribution of housing units in each neighbourhood remained constant across the years.

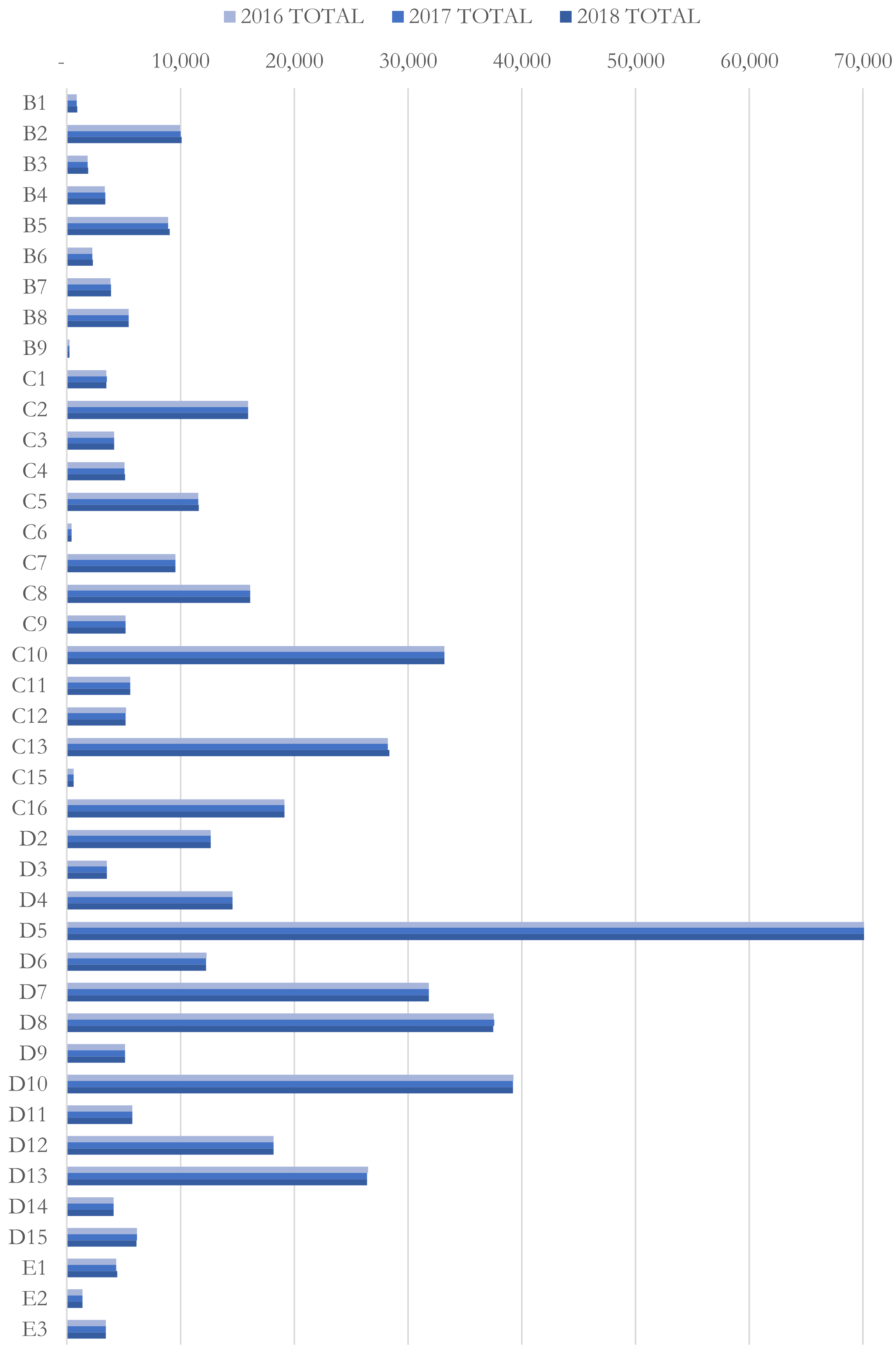

Figure 3.3. Residential properties in the city of Turin by OMI area, 'A' category data excluding offices (A10). Source: OMI.

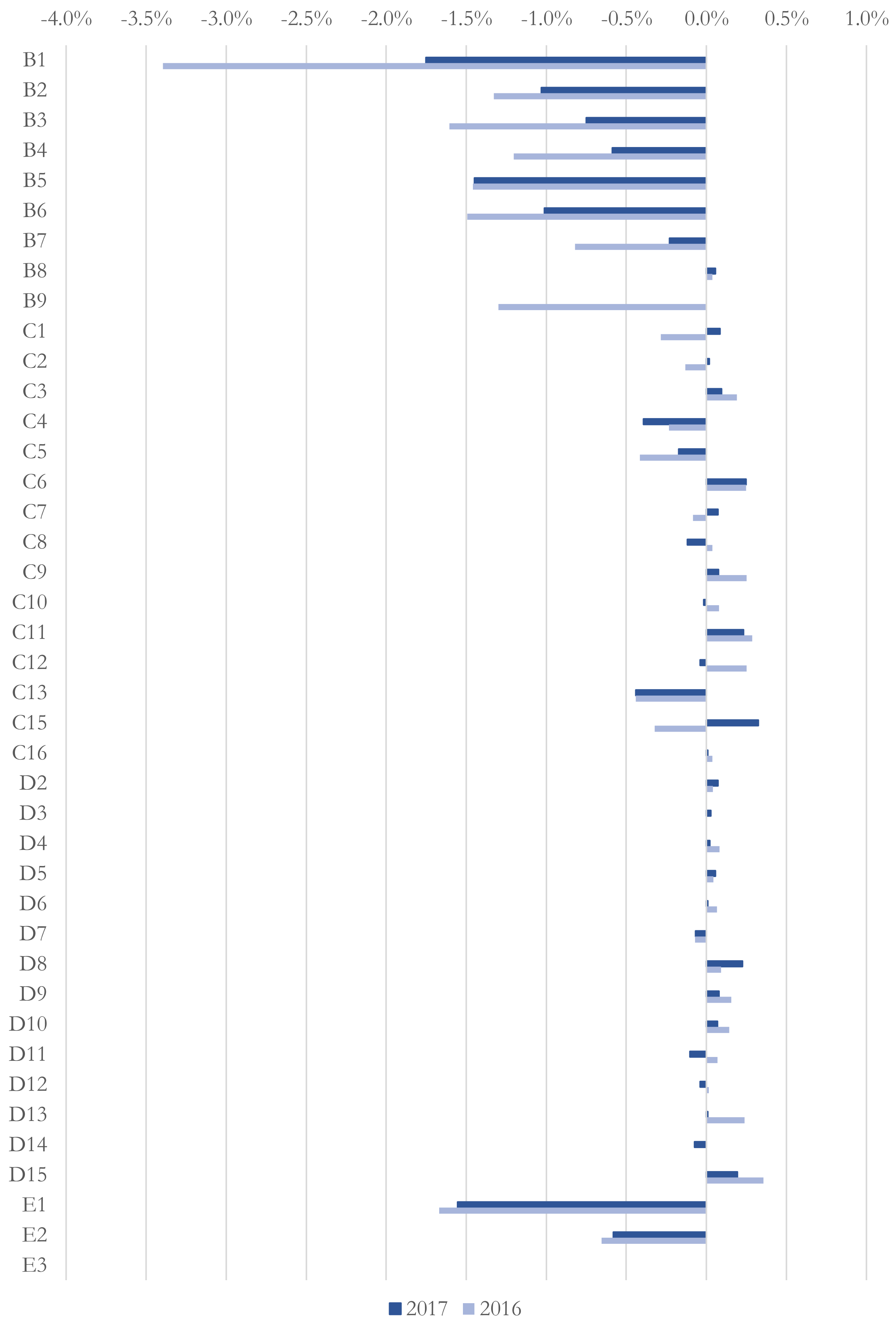

Figure 3.4. Variation in total number of housing units registered in 2016 and 2017 relative to the estimated stock in 2018.

These figures can be rearranged to have the number of housing units attributable to Idealista neighbourhoods. Using the matrix described in 3.1.4, it is possible to obtain the values in Figure *3.5*, which refer to 2018 only. Using values from only one year is sufficient in this case, since the number of buildings and houses do not change significantly over time, particularly in a city where the population is not increasing.

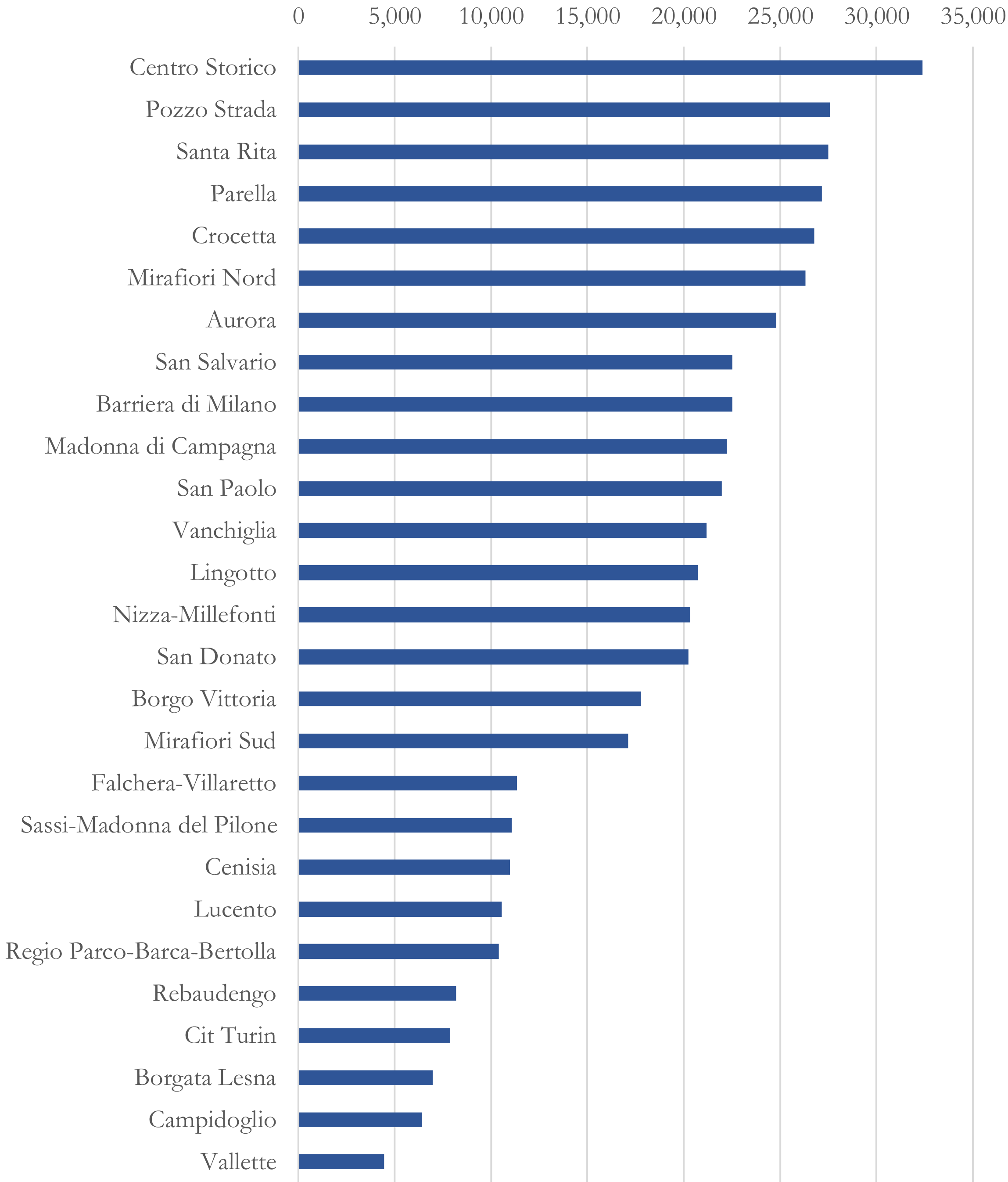

Figure 3.5. Number of 'A' category properties (excluding A10) found in each Idealista neighbourhood, 2018 OMI data.

A heat map with these figures is shown in Figure *3.6*. The differences one may find with Figure *3.2* only depend on the different design of boundaries in the two maps.

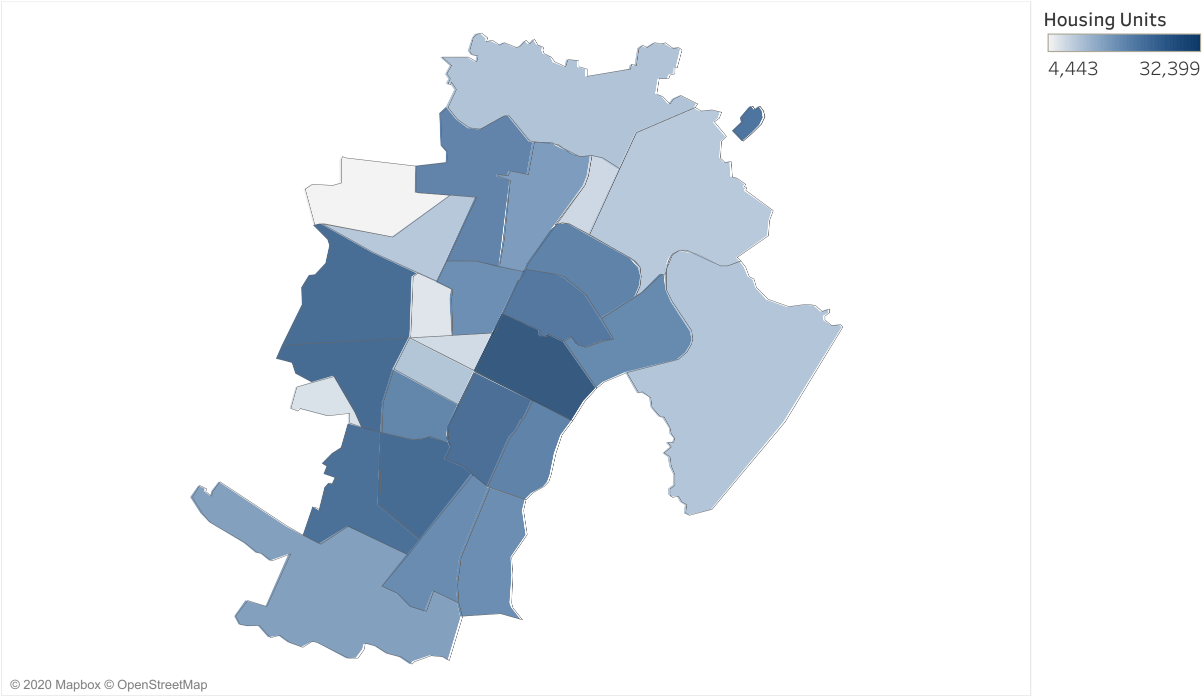

Figure 3.6. Housing units by Idealista area in the city of Turin, 'A' category excluding offices (A10).

Now that housing units have been attributed to Idealista neighbourhoods, it is possible to investigate what type of properties are usually found in the different areas. The stack bars in Figure 3.7 show the number of units belonging to the main cadastral categories, which are the following (note that "Other" includes the categories A06, A07, A08, A09 and A11):

A01	*Abitazioni Signorili*	Higher-class homes
A02	*Abitazioni Civili*	Regular homes
A03	*Abitazioni Economiche*	Economical homes
A04	*Abitazioni Popolari*	Public housing homes
A05	*Abitazioni Ultrapopolari*	Homes with a lower quality than A04
A06	*Abitazioni Rurali*	Rural homes
A07	*Abitazioni in Villini*	Small villas
A08	*Abitazioni in Ville*	Higher-class villas
A09	*Castelli e Palazzi artistici o storici*	Castles and historical buildings
A11	*Abitazioni Tipiche dei luoghi*	Typical homes

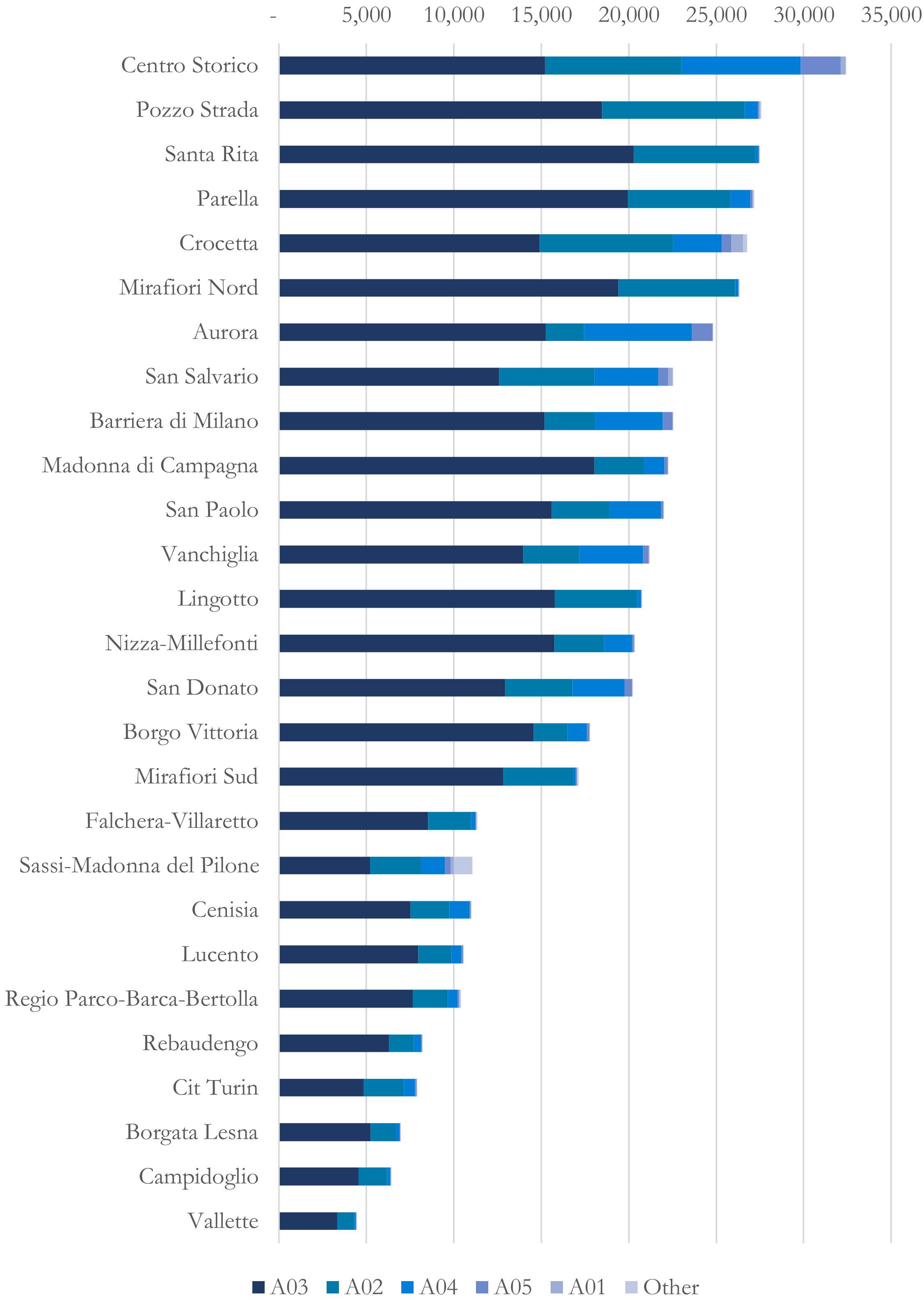

Figure 3.7. Composition of Idealista neighbourhoods by property type.
Source: OMI data, 2018.

As the graph shows, the most widely diffused category is A03, followed by A02 and A04, while the remaining classes make up a very small share of the number of housing units. The dataset used for these graphs provides the total number of square meters for each property category which, using the number of housing units belonging to each category, can be used to estimate the average dimension of homes. Weighing these 'category dimensions' for their percentage on the total stock in the city, 91 m^2 happens to be the average dimension of a home in Turin (using 2018 data).

3.2.2 Price Trends

Using the data provided for each semester, it is possible to calculate the average prices registered in the city. Since the values provided refer to OMI areas and there often is a distinction between the different property categories, it is necessary to take these into consideration.

For each district, an average value was calculated on the basis of the number of properties belonging to each property type, following the classification in Table 2. For instance, if we have the average price of *Ville e Villini* for the neighbourhood D5 in the first semester of 2017 (S1 2017), this price is going to contribute to the average price of D5 in S1 2017 for a percentage that is proportional to the number of housing units attributable to that property type out of the total number of housing units in D5.

Property Type	**Cadastral Categories**
Abitazioni Signorili	A1
Abitazioni Civili	A2
Abitazioni di tipo Economico	A3, A4, A5, A6, A9, A11
Ville e Villini	A7, A8

Table 2. Cadastral categories belonging to each property type.

Unfortunately, some data are missing or unavailable, and at times there are neighbourhoods where the percentage of housing units belonging to a certain category is relevant but there is no price data for it. Whenever this happens, the price used is the one referring to *Abitazioni Civili,* since it is available for every OMI area at any time.

Once an average price for each neighbourhood is available, it is possible to find the average price for the entire city semester by semester. To do this, neighbourhood values have been weighted using the number of housing units in each OMI area, obtaining the two graphs below. The same process was followed to find the values of rents and selling prices.

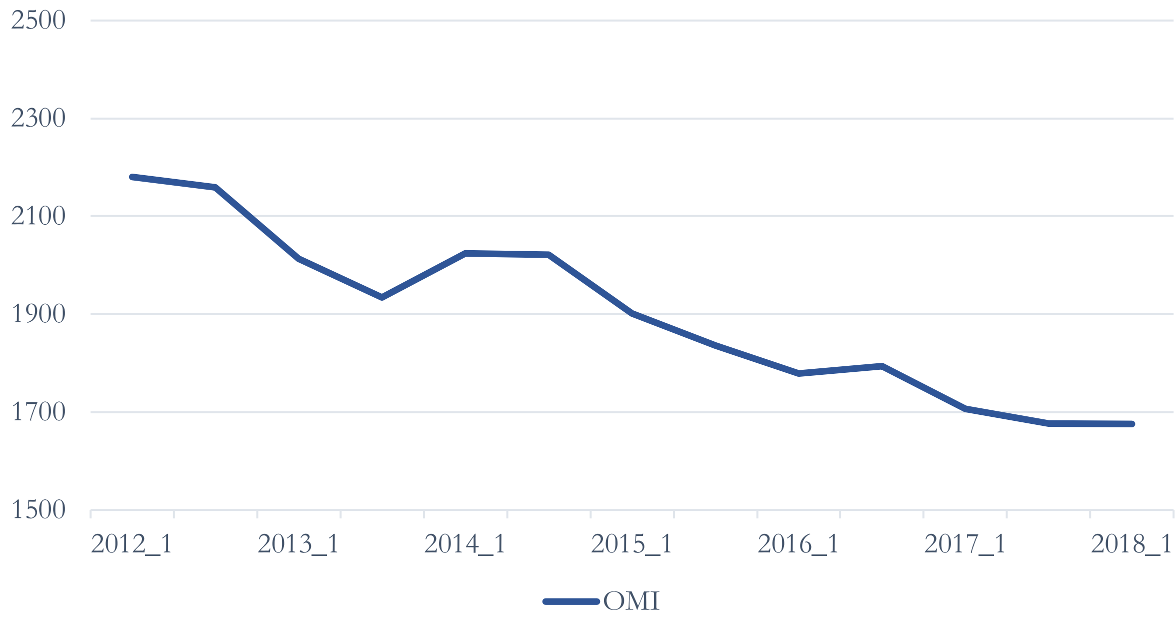

Figure 3.8. Average selling prices in Turin (€/m²), aggregation of OMI semesterly data.

The line plotted in Figure *3.8* shows a descending trend in property prices throughout the city. Starting from an average selling price of approximately 2180 €/m² at the beginning of 2012, prices have fallen to a minimum of 1675 €/m² in the first semester of 2018: a 23% drop.

Monthly rents, on the other hand, hovered at 8,30 €/m² throughout 2012, and fell to a minimum of 7,21 €/m² in 2016 (see Figure *3.9*). Since then, a slight increase brought the average price at 7,31 €/m², which translates into a 12% drop since 2012.

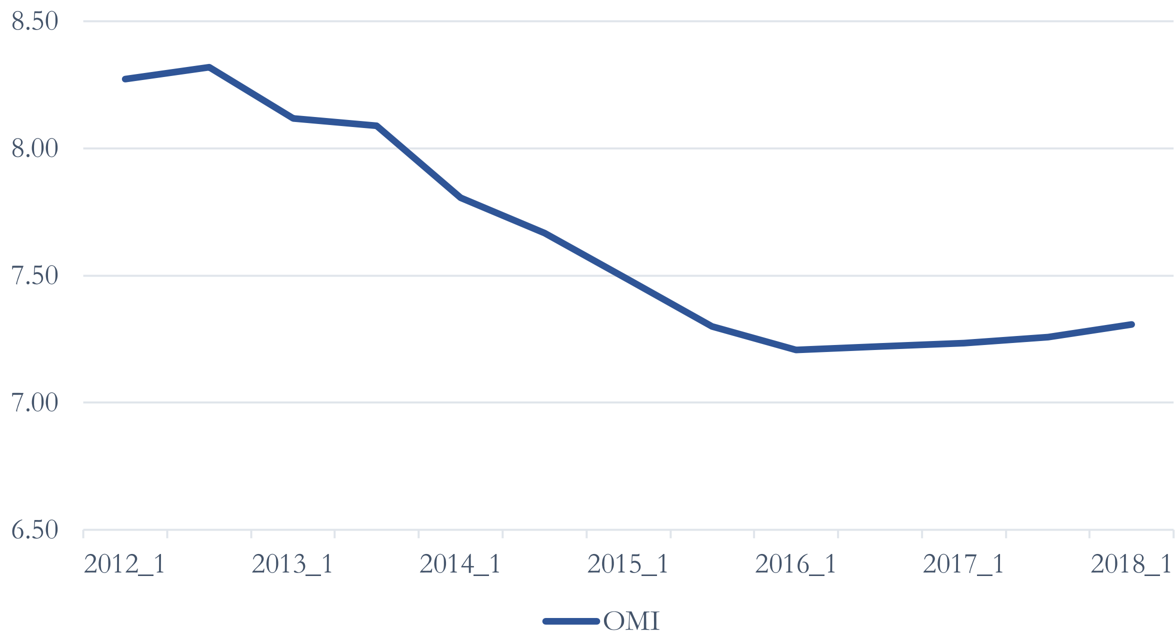

Figure 3.9. Average monthly rents in Turin (€/m²), aggregation of OMI semesterly data.

3.3 Airbnb Analysis

3.3.1 The characteristics of listings

To analyse city-specific data on Airbnb, it is best to start from the composition of listings and their evolution over time. The graph in Figure *3.10* shows the total number of available listings in each quarter grouping them by listing type. From 2014 to 2019, the number of listings has grown for each of the 4 categories, even if shared rooms and hotel rooms remained a minority throughout the period.

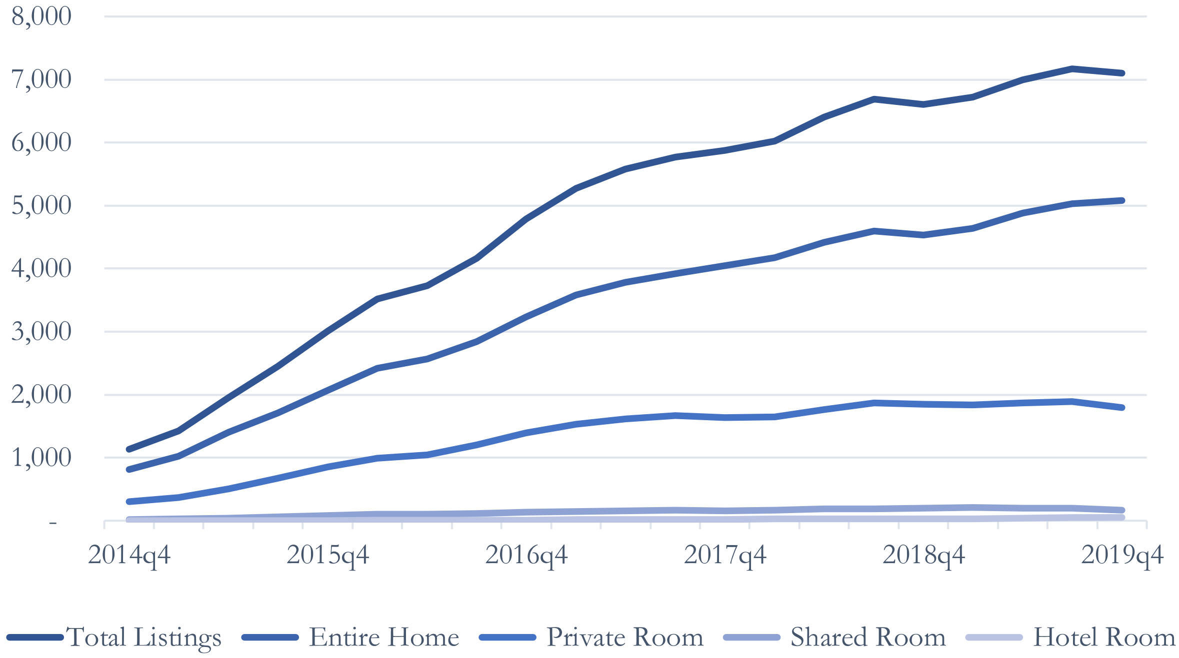

Figure 3.10. Number of listings by listing type in the city of Turin from Q4 2014 to Q4 2019.
Source: AirDNA, quarterly.

Taking into account each listing type's share on the total amount of listings quarter by quarter (Figure *3.11*), it is possible to see that the composition of supply has not changed much. Approximately 70% of listings consisted of entire homes, and about 27% of private rooms. Shared rooms and hotel rooms have been far less popular, consistently making up less than 5% of combined supply throughout the period.

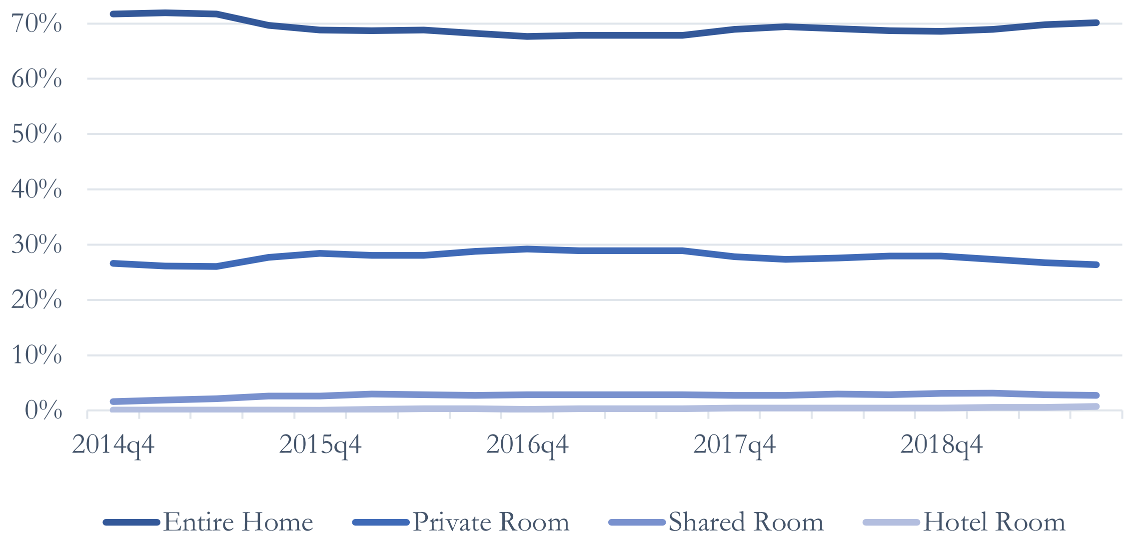

Figure 3.11. Quarterly composition of listing by property type in Turin.

On average, 2019 presented the following percentages:

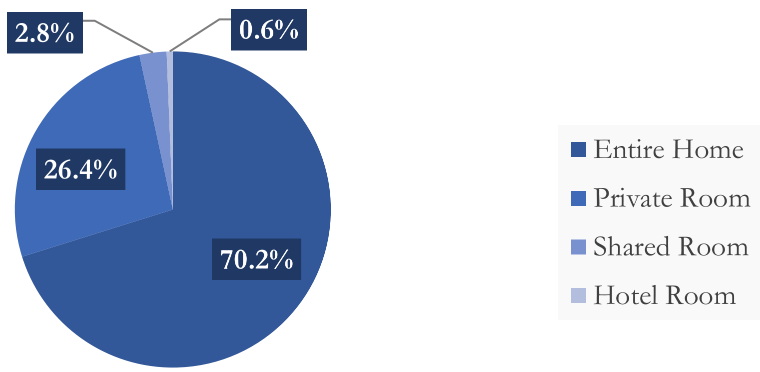

Figure 3.12. Average composition of listings by property type in 2019.

Although these numbers are aggregated measures referring to the city as a whole, it is interesting to see that each neighbourhood presents a different composition of listings. As Figure

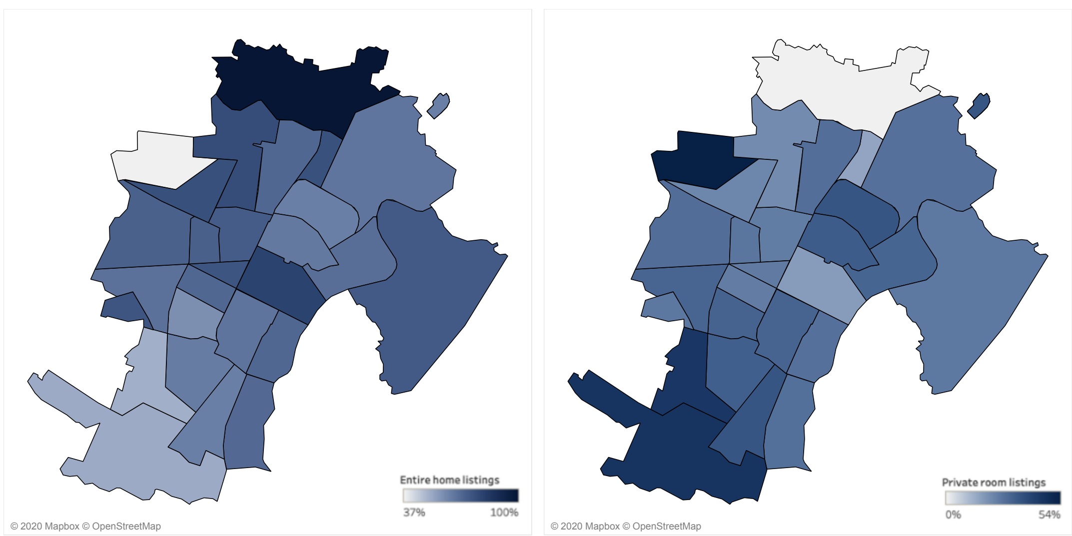

Figure 3.13. Map showing the prevalence of listing types in the city's neighbourhoods.

3.13 and Figure *3.14* show, in some areas 75% of supply is made up of entire apartments, while other neighbourhoods have a larger share of private rooms.

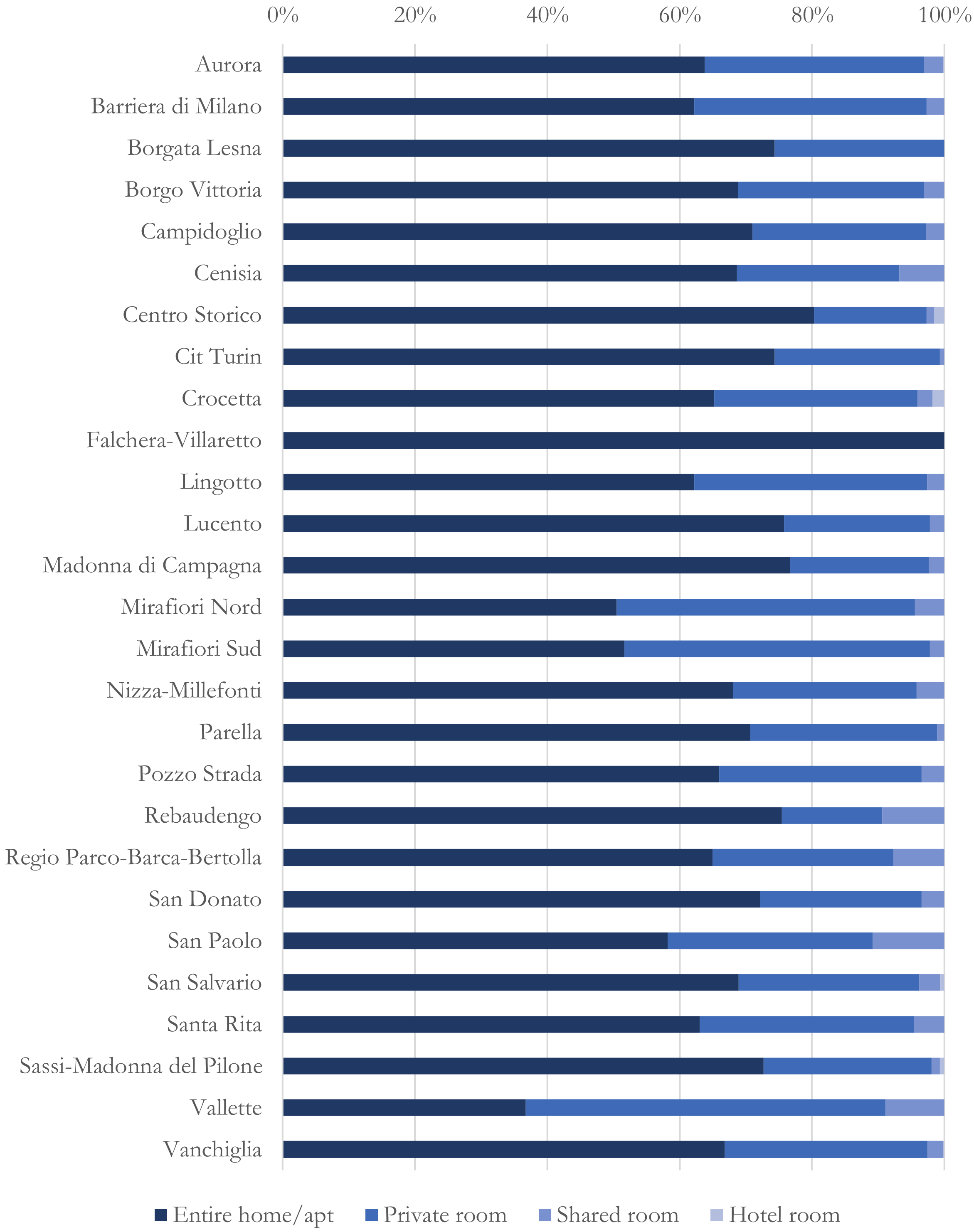

Figure 3.14. Supply composition in each neighbourhood by listing type. Data calculated as 2019 average.

It is important to remember that Airbnb was born to offer spare beds and rooms to those who could not find accommodation through conventional channels such as hotels or hostels. However, by looking at these graphs, supply seems to have followed other dynamics in certain neighbourhoods. Indeed, one could assume that hosts initially advertised spare homes, thus allowing these underutilized to produce a stream of income. If this were to be the norm, the number of listings should not have increased too much over a 5-year period, but a fivefold increase in the number of entire homes advertised on the website clearly shows that many owners may have decided to either move their offering from the long-term rental market to short-term rentals or to buy homes for the sole purpose of making money through Airbnb.

3.3.2 The distribution of listings in the city

The distribution of listings throughout the city is not even. In Turin, for example, Airbnb properties are mostly located in central areas, particularly in the neighbourhood identified as *Centro Storico* by Idealista, which is represented by the darkest area in Figure *3.15*. Suburban areas have a significantly lower number of listings as one would expect in a large city where the main attractions are not scattered outside central neighbourhoods.

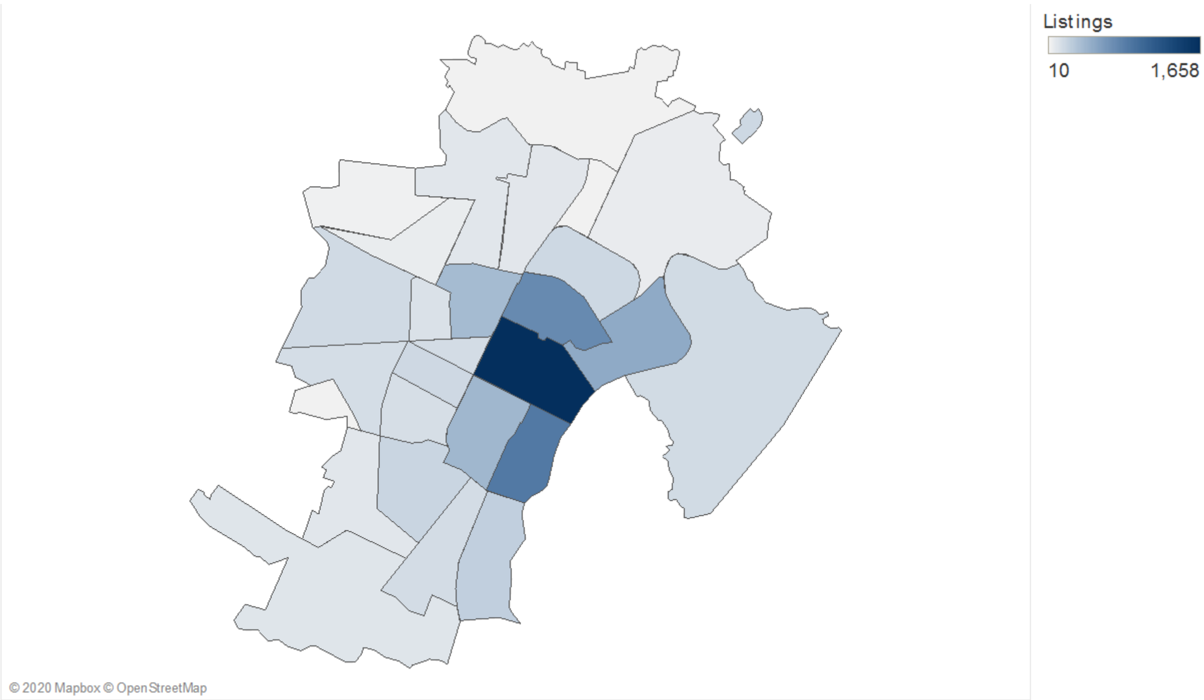

Figure 3.15. Number of listings by Idealista neighbourhoods in Turin, 2019 average.

Some data is missing from the map since it was not possible to assign it to any neighbourhood. The number of observations presenting this issue is relatively low so the impact is negligible. Considering the number of listings in relation to the housing units in each neighbourhood, it is possible to create a more precise map where each neighbourhood is coloured using this metric, which can be interpreted as 'Airbnb intensity' (Figure *3.16*). For the city as a whole, Airbnb listings in 2019 have on average consisted of 1,4% of total stock, up from 1,3% in 2018. As illustrated in Figure *3.15*, it is clear that Airbnb penetration is higher in central areas, with neighbourhoods such as *Centro Storico* (which is the darkest portion of Figure *3.16*) having more than 5% of their housing units advertised on the platform.

The time evolution of Airbnb density values for each neighbourhood is shown in Exhibit 3.

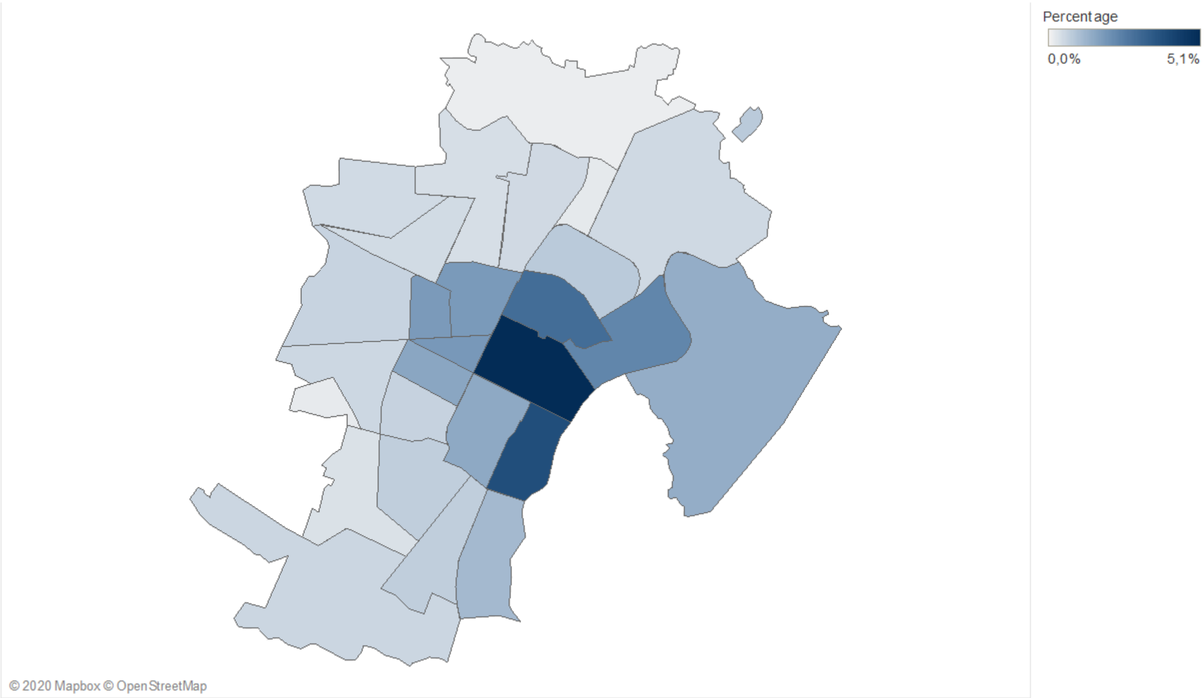

Figure 3.16. Percentage of housing units listed on Airbnb on average in 2019.

Taking into account the number of listings, the top 6 neighbourhoods by this metric included approximately 67% of total supply for the city in 2019. The absolute number of properties on Airbnb for each of these neighbourhoods has steadily grown year on year (see Figure *3.17*), but more slowly compared to the rest of the city. Indeed, the share of properties located in *Centro Storico* has decreased from 31% to 24% of the total, while the other 5 neighbourhoods' share remained virtually unchanged (see Figure *3.18*).

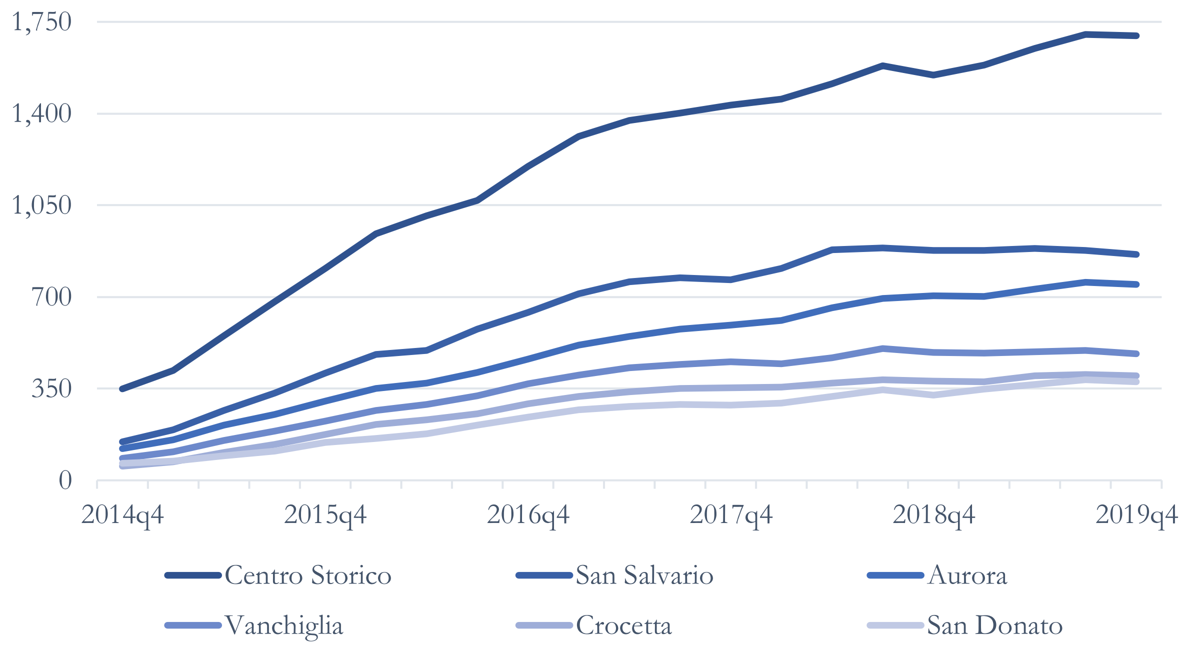

Figure 3.17. Total number of listings by Idealista neighbourhood in Turin, quarterly data. Only the largest neighbourhoods by number of listing are shown.

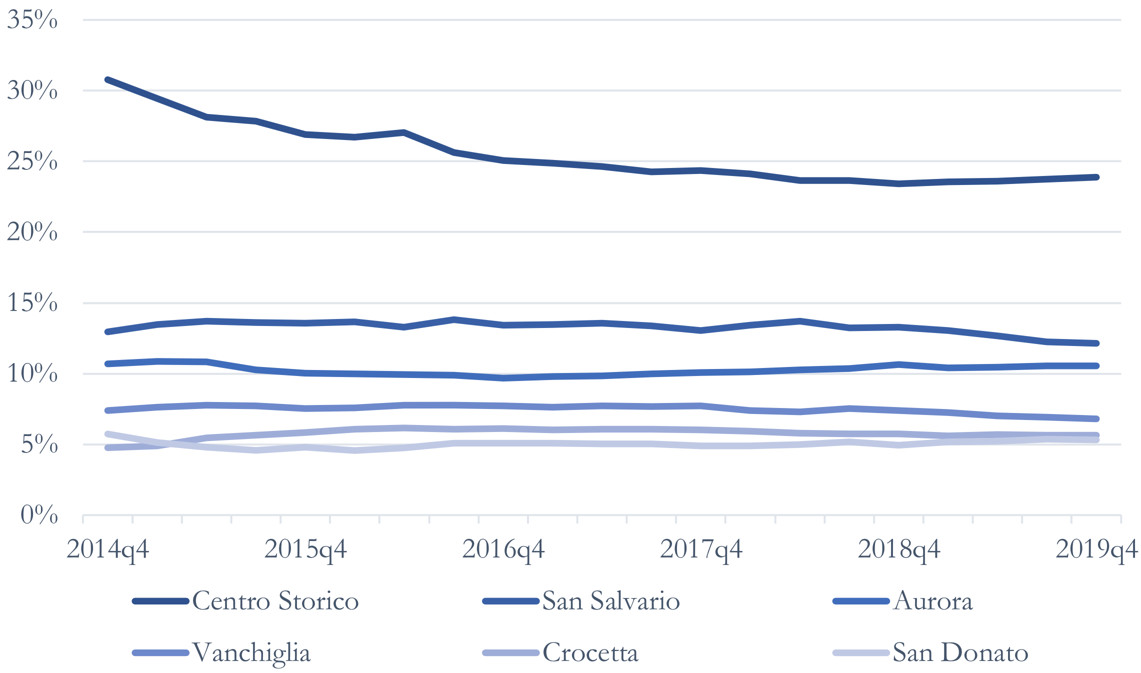

Figure 3.18. Share of listings located in each of the top 6 neighbourhoods by listing number, quarterly data.

The following table shows how the percentage of listings in central areas decreased over the last 5 years[14] from 72,7% to 66,9%.

Year	2015	2016	2017	2018	2019
Share of total listings	72,7%	70,8%	69,0%	68,1%	66,9%

Table 3. Share of total listings found in the top 6 neighbourhoods of Turin, yearly average.

What is interesting about this decline is that it may stem from a variety of causes, perhaps lower occupancy rates, a lower profitability or simply an increase (or the discovery) of demand in peripherical neighbourhoods; these are to be discussed in the next paragraph.

3.3.3 Multi-property hosts, occupancy rates and supply

After having seen the main characteristics of listings by looking at their location and composition, it is time to consider their productivity, which means focusing on how much money hosts can make and how supply and demand have evolved over time. These considerations start from Figure *3.19*, which shows the number of hosts listing only one property against those listing, thus probably also owning, more than one. Researchers investigating the Airbnb phenomenon usually refer to the latter as *commercial hosts* or *commercial listings*, since those who only own one property may actually be sharing excess capacity through the platform, while the others are likely investing in this capacity to make money. Also, someone owning more than one property is more likely to either dedicate a lot of time to their management or to employ someone to do it. Either way, the activity can be considered commercial in the sense that it is structured to provide a service on a continuous basis and not only as a side activity. To be sure, also some of the hosts owning one

[14] 2014 data has been omitted because only the fourth quarter was available.

property may be conducting a sort of commercial activity by dedicating a lot of their time to it and renting their excess capacity throughout the calendar year. However, it is best to distinguish between commercial and non-commercial listings by looking at the number of properties belonging to the owner, as it is the most objective way.

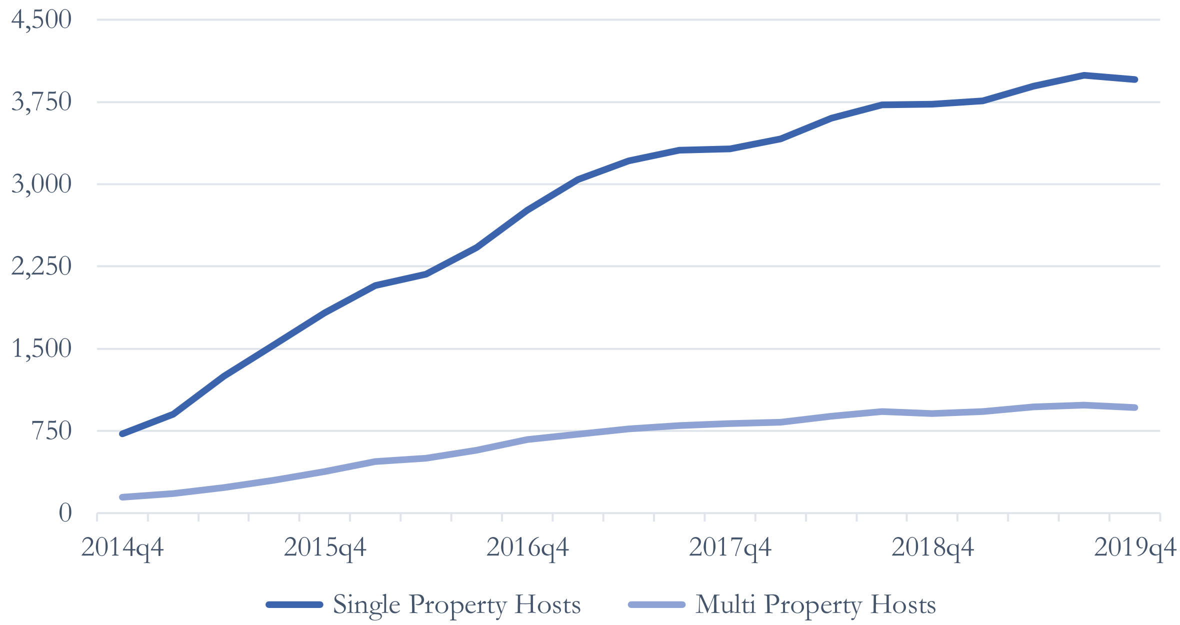

Figure 3.19. Graph showing the number of hosts owning only one property against those owning more than one. “Hotel room” listings have been discarded.

In 2019, the share of hosts that owned more than one property was just under 20%, while the remaining 80% only listed one property on Airbnb. As the graph shows, these figures have not changed significantly from 2016 until now, while in the first two years for which the data is available, multi property hosts were consistently less than 17%. On the other hand, the percentage of listings belonging to multi-property hosts has risen over time, from approximately 35% at the end of 2014 to over 43% in the last quarter of 2019, when the average commercial host posted 3,2 listings. In a nutshell, commercial owners have been buying (or listing) more properties over time, suggesting that Airbnb is a highly profitable platform for its hosts. Interestingly, both the figure referring to the number of hosts owning a single property and the number concerning the total amount of listings belonging to each host type are very similar to the ones Horn & Merante (2017) found for Boston. Indeed, their figures were 18% and 46% compared to 20% and 43% found for Turin. On the other hand, in Barcelona 61% of all listings belonged to commercial hosts (Segù, 2018).

After having invested in “hosting capacity”, how much of this capacity are the hosts able to make use of? AirDNA provides an occupancy rate for each listing with at least one booked night during the observation period. With Stata, it is possible to calculate an aggregate average occupancy rate for each neighbourhood quarter by quarter. To have an easy-to-read graph, 3 different indicators have been calculated, on a yearly basis, to identify potential changes in the occupancy rates: "Total" refers to the entirety of neighbourhoods, "Top 3 Neighbourhoods" refers to the 3 neighbourhoods with the highest number of listings, and "Bottom 24 Neighbourhoods" to the ones with fewer listings. Data on the average number of listings in each neighbourhood in a given year has been used to weigh the occupancy rates for the 3 indicators.

The results are shown in Figure *3.20*, where it is possible to see a steady increase in occupancy rates for each of the indicators, all of them at least doubling their value from 2015 to 2019. Moreover, the difference between the occupancy rates in central neighbourhoods (which are those included in the top 3) and the rest has narrowed over time, from approximately 3,5% in 2015 to a little over 2,5% in 2019.

Figure 3.20. Average yearly occupancy rate.

Considering occupancy rates for listing type, we are able to determine what guests tend to prefer and if this preference has changed over time (see Figure *3.21*). Including listings classified as "hotel rooms" in the dataset to see if there is any substantial difference with the remaining listing types, hotel rooms appear to behave in a different way from an occupancy rate point of view. Indeed, these rooms represent a very small percentage of listing in the original dataset and, given their different dynamics, it is best to discard them from the analysis both here and in Chapter 4. Considering the rest, it is possible to see a seasonal variation in occupancy rates, with higher rates in the fourth quarter and lows during the first quarter of each year. Lower occupancy rates for shared rooms help explain a relatively low share of listings for this type of accommodation, which is probably the last to be chosen by potential guests.

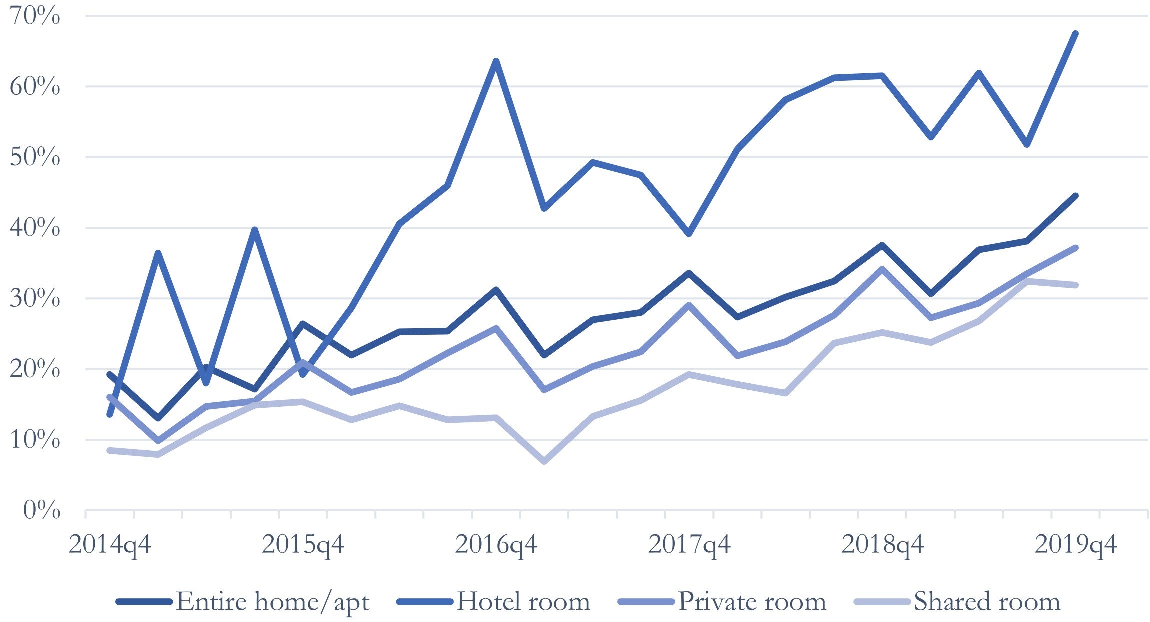

Figure 3.21. Quarterly occupancy rates for each listing type.

Data in the previous two graphs include any listing in the dataset, even those where the price asked by the host is disproportionately above the market price or listings that are considered active but are poorly managed. In fact, a closer look at the data reveals that many listings have occupancy rates as low as 0%, which can stem from wrong pricing policies, low host engagement when a guest wishes to book but needs his approval and, obviously, a low-quality listing (a bad position, few pictures, no comforts). To temporarily exclude these listings from the dataset in order to better search for differences among neighbourhoods and listing types, it is possible to filter the dataset to only include listings that have had an occupancy rate of at least 10% in each quarter, an arbitrary value chosen for this purpose only. The new graphs are shown in Figure *3.22* and Figure *3.23*.

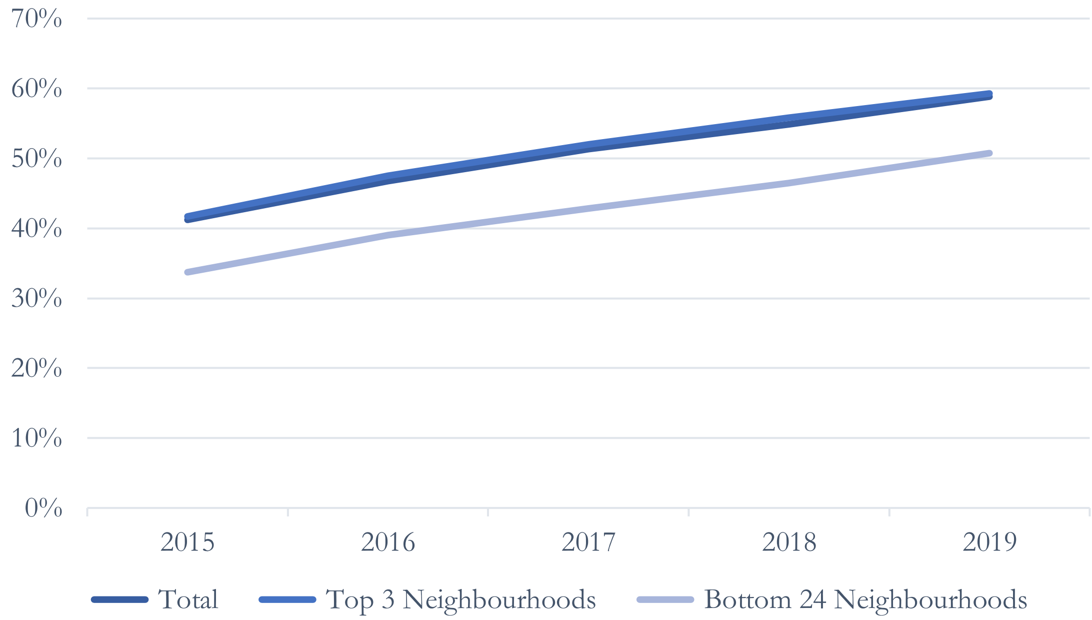

Figure 3.22. Average yearly occupancy rate for listings with an occupancy rate of at least 10%.

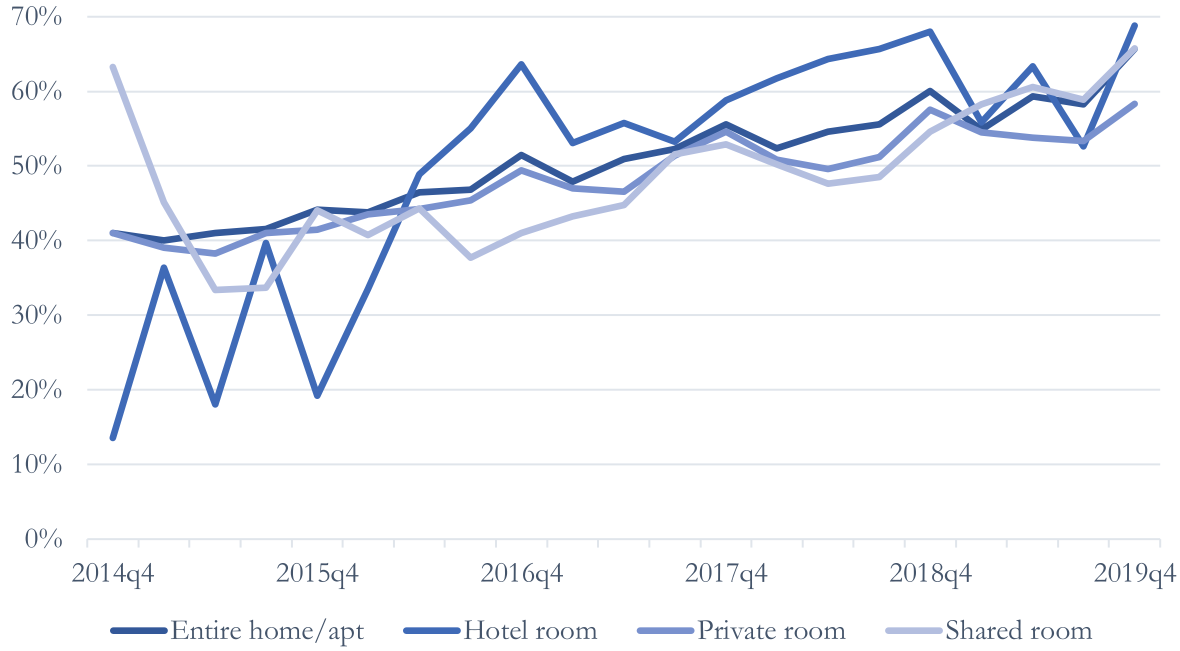

Figure 3.23. Quarterly occupancy rates for each listing type for listings with an occupancy rate of at least 10%.

The top 3 neighbourhoods keep on having higher occupancy rates compared to the rest of the city. The two trends are also very similar, and the gap between the two groups goes from 8% in 2015 to 8,5% in 2019. Among the different listing types, occupancy rates are similar as well. Moreover, the difference between hotel rooms and the remaining listing types is now significantly lower than in Figure *3.21*, suggesting that hosts who care about their listings can reach very high occupancy rates, comparable to the ones obtained by some hotels. However, it is worth remembering that an occupancy rate of 50% in a quarter does not mean that the listing was booked 45 days out of 90. In fact, the occupancy rate refers to the amount of time the listing was made available by the host (see 3.1.1 for the formula). Thus, an occupancy rate of 50% could even mean that a listing was booked for only 3 nights (if the initial availability was a mere 6 days) so its profitability may be very low. However, the median number of blocked days never exceeds 25 days in any of the quarters.

The average stays booked by guests are approximately 4 to 7 nights long throughout the observing period, while the median swings from 3 to 5 nights. Both statistics have small variations among listing types, and year quarters. However, the general tendency is shorter stays in private homes and longer stays in shared rooms, but this could be attributable to the restricted number of listings satisfying this criterion.

Setting the discussion on the average length of stays aside, Figure *3.24* shows the evolution of the number of nights offered on the platform for the city of Turin, which allow for the identification of changes in supply and help understand host behaviour. In fact, occupancy rates and the number of active listings is not enough to determine supply and other variables have to be taken into account. The data presented have been extracted by selecting each of the three possible statuses a listing-specific calendar day can have on the platform. The 3 conditions correspond to an available, reserved or blocked listing, and the number of days for each status are found with the variables `AvailableDays`, `ReservationDays` and `BlockedDays`, respectively. Just as was pointed out in Figure *3.21* for occupancy rates, the number of reserved nights presents a seasonal trend: demand decreases during the first quarters and hits a local maximum in the fourth quarters, most likely thanks to the winter holidays. The number of active listings in a quarter does not correspond to supply because hosts can decide to block the majority of days, significantly reducing the choices available to guests. The line plotting the number of blocked nights clearly shows the entity of this phenomenon, as blocked nights always exceed reserved nights.

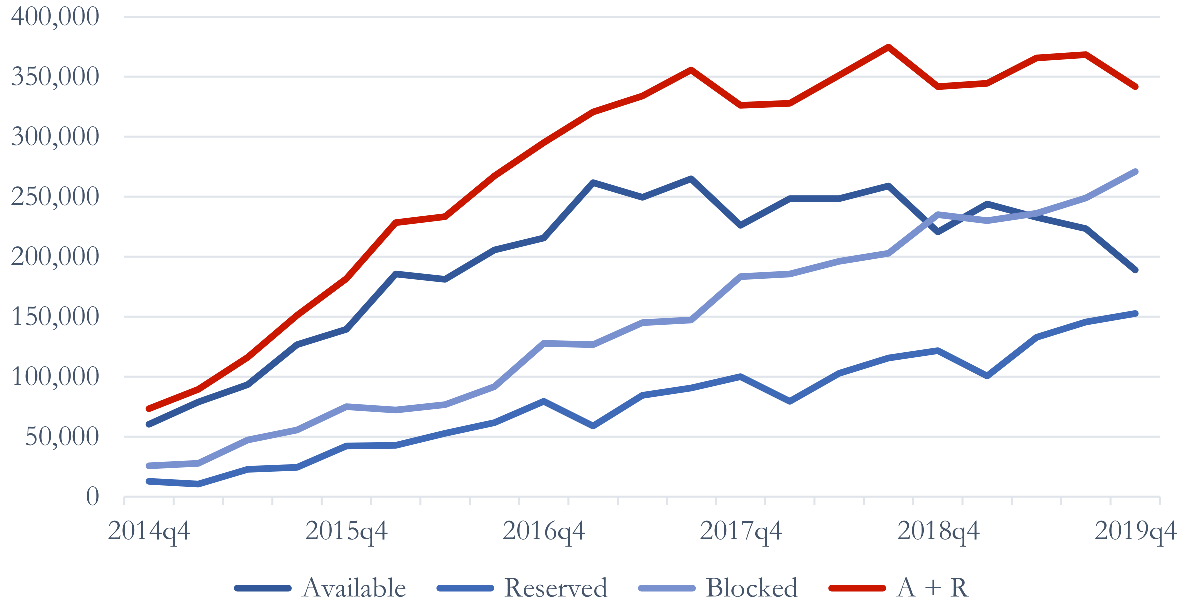

Figure 3.24. Total number of available, reserved and blocked nights, quarterly data. The red line shows the sum of available and reserved nights.

Table *4* shows how the same 3 statuses change depending on the listing type, rising further considerations. First of all, it is possible to see that the distribution of available nights among the different listing types has not changed between 2015 and 2019. On the contrary, the distribution of reservations suggests a small change in guest preferences: the percentage of booked nights that involve entire homes has risen from 2015 to 2019, which may signal that the use of Airbnb is becoming more common among people who would have otherwise booked a hotel room. It is also interesting to observe that entire homes accounted for a little more than 67% of supply in both 2015 and 2019, but the share of reserved nights for this listing type have always been well over 75%, suggesting a stronger demand for this listing type. In fact, the opposite is true for the share of reserved nights in private and shared rooms, which are reserved less than they are offered.

Blocked nights, however, present a higher variability. Entire homes, which accounted for slightly more than 67% of supply in both 2015 and 2019, have represented 70,4% of blocked nights in 2019, while in 2015 the figure was higher: 74,2%. This may mean that a greater number of entire homes are being listed as commercial activities. On the other hand, private and shared rooms have had an increase in the relative number of blocked nights.

	Listing Type	2015	2019
Available Nights	Entire home	67,5%	67,2%
	Private room	29,8%	29,8%
	Shared room	2,7%	3,0%
Reserved Nights	Entire home	75,1%	77,5%
	Private room	23,2%	20,8%
	Shared room	1,8%	1,7%
Blocked Nights	Entire home	74,2%	70,4%
	Private room	24,0%	26,5%
	Shared room	1,8%	3,1%

Table 4. Distribution of available, reserved and blocked nights by listing type in 2015 and 2019.

Having established that there is an excess of supply, how can it be quantified? Since listings are either marked as available (A), reserved (R) or blocked (B), it is reasonable to identify the excess of supply with the number of available nights. Grouping data on the total number of nights and considering the available nights year by year, it is possible to see how the share of available nights on the total has diminished in the period 2015-2019 (see Table 5). The number of listings has increased during the same period, so there has not been a reduction in offered capacity but rather a catch up by demand, which has risen faster than supply. Nevertheless, supply is still higher than real demand.

	Available Nights	Total Nights (A+R+B)	Percentage of Available Nights
2015	438.589	743.716	59,0%
2016	788.436	1.392.826	56,6%
2017	1.002.425	1.939.117	51,7%
2018	976.408	2.216.147	44,1%
2019	889.359	2.407.030	36,9%

Table 5. Absolute and relative number of nights on the platform, yearly data.

The next question that may come in mind is whether there are any differences between single property and multi-property (or commercial) hosts. Multi-property hosts provided a total of 2.622.438 nights from the last quarter of 2014 to the end of 2019, while single property hosts provided 3.167.281 nights (54,7% of the total).[15] The commercial nature of multi-property hosts is visible when looking at blocked nights, since for every night that is either available or reserved, the corresponding number of blocked nights in listings owned by commercial hosts is significantly lower than for single property hosts. Figure *3.25* has been created by aggregating yearly data for the two type of hosts; then, the number of blocked nights was divided by the sum of available and reserved nights. Specifically, in 2019 single property hosts blocked 0,82 nights for every night that was being provided (thus either marked as available or reserved). On the other hand, commercial hosts only blocked 0,55 nights, indicating that their listings were more frequently 'on the market'[16], a necessary condition if the goal is to have a stream of income.

Blocking 0,55 nights can be seen as counterproductive from this point of view, but it is possible for the figure to be much smaller. Indeed, a night may be blocked because the host managed to obtain a reservation on another platform, or the host and the guest were able to reach an agreement outside the Airbnb platform. This phenomenon is very difficult to quantify, but the incentives to put it in place belong to both parties, since the absence of fees can considerably reduce the price paid by the guest while increasing the income of the host, for whom it is easier to avoid taxes. Of course, peer-to-peer platforms enforce trust among participants, but if a 10-day booking is settled for 3 days via Airbnb and the rest outside the platform, the mechanism is still at work.

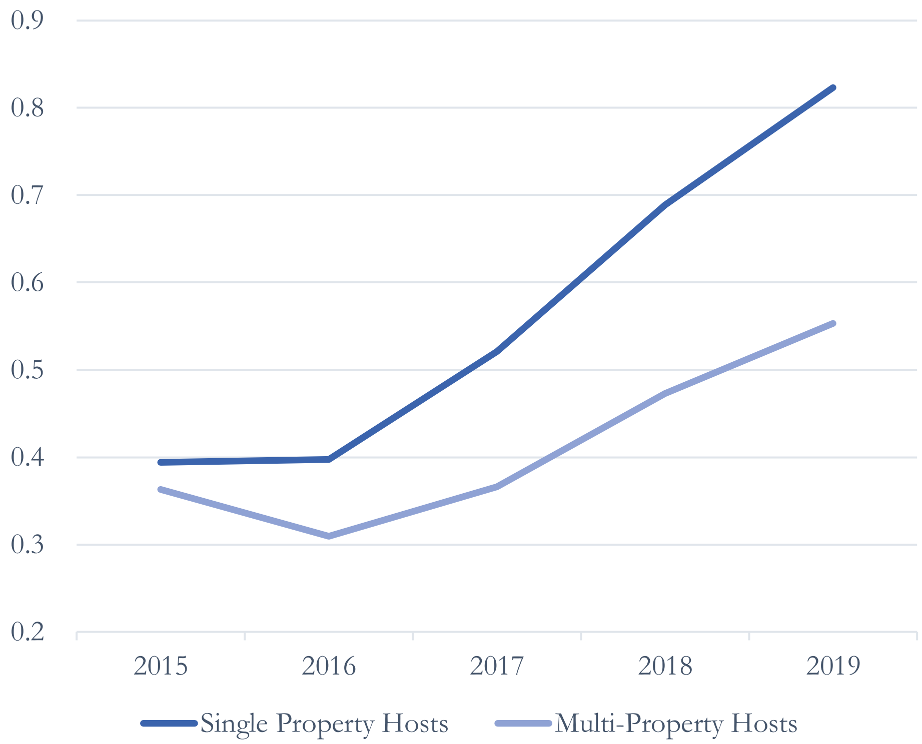

Figure 3.25. Number of blocked nights for each night that is either available or reserved, yearly average.

[15] These values have been calculated considering the sum of available and reserved nights, excluding blocked nights.

[16] Note: *blocked nights* may also refer to nights that have been booked via other means or platforms. Thus the 0,55 figure may be much smaller, but the data provided does not allow for further considerations.

3.3.4 Revenues

The last part of the analysis on data provided by AirDNA focuses on the profitability of listings, here intended as the gross revenues a host is able to obtain in a period of time. The available data include two different measures, which can be classified as real revenues and fictious revenues. The first are described by the variable `Revenue`, and report the amount of money (in euros) a host has made during a specific quarter, including the cleaning fees paid by guests and the transaction fees that are to be paid to the platform. Fictious revenues are the ones referring to the prices requested by hosts for a listing, and are described by the variables `PublishedNightlyRate`, `PublishedWeeklyRate`, and `PublishedMonthlyRate`. For the purposes of this analysis, only the real revenues have been taken into account, since many published rates have been found to be exceptionally high.

In the first data extractions, average revenues were calculated for each listing type, but the resulting values were very low and seemed inconsistent with expectations. In fact, considering the entirety of listings included in the database is not a good approach, since many listings fail to obtain any bookings in certain periods of time and their revenues are classified as €0 over the period, leading to a bias. To overcome this issue, it is advisable to select only the listings that have obtained at least a booking in the period. To do so, it is enough to consider the listings that reached at least an occupancy rate of 1% during a specific quarter which, in the event that the listing was available for 3 full months, equals to bookings that were reserved for at least a day. Figure *3.26* shows the average quarterly revenue obtained for these listings.

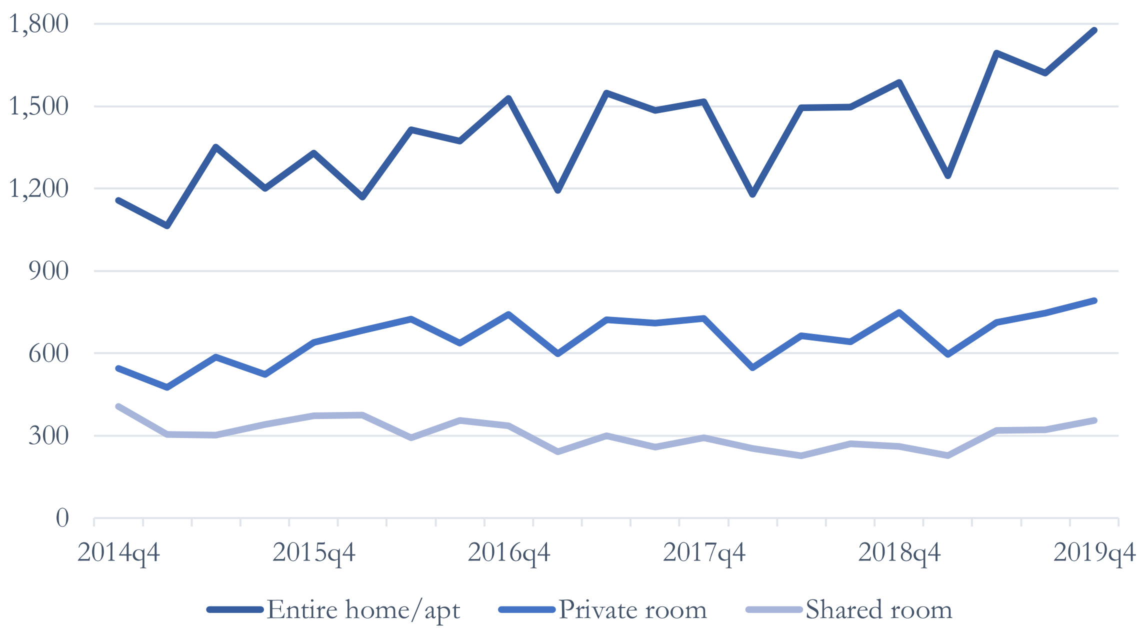

Figure 3.26. Average gross revenue by listing type. Quarterly data referring to listings with an occupancy rate of at least 1%.

As one would expect, entire homes are much more profitable than the other listing types and the average revenue follows a seasonal trend that counters the seasonal trend found for available listings (shown in Figure *3.24*). Indeed, revenues are the highest during fourth quarters, which is when availability decreases (see the red line in Figure *3.24*), and drop during the first quarters of every year, which in Figure *3.24* correspond to low reservations periods (see the "Reserved" line in the graph).

The values represented in the previous graph are good for having a general idea about what to expect from a listing on Airbnb, they are affected by a number of problems. First, these values are averages that refer to listings that may be available for both long and short periods of time, and second, they are aggregate measures that depend on occupancy rates; thus, it is difficult to determine the minimum number of bookings needed to make Airbnb more profitable than the long-term market. To have a more accurate measure, quarterly revenues have been divided by the number of reservation days, so that a revenue per booked night was calculated. Figure *3.27* shows the average revenue per booked night for each listing type.

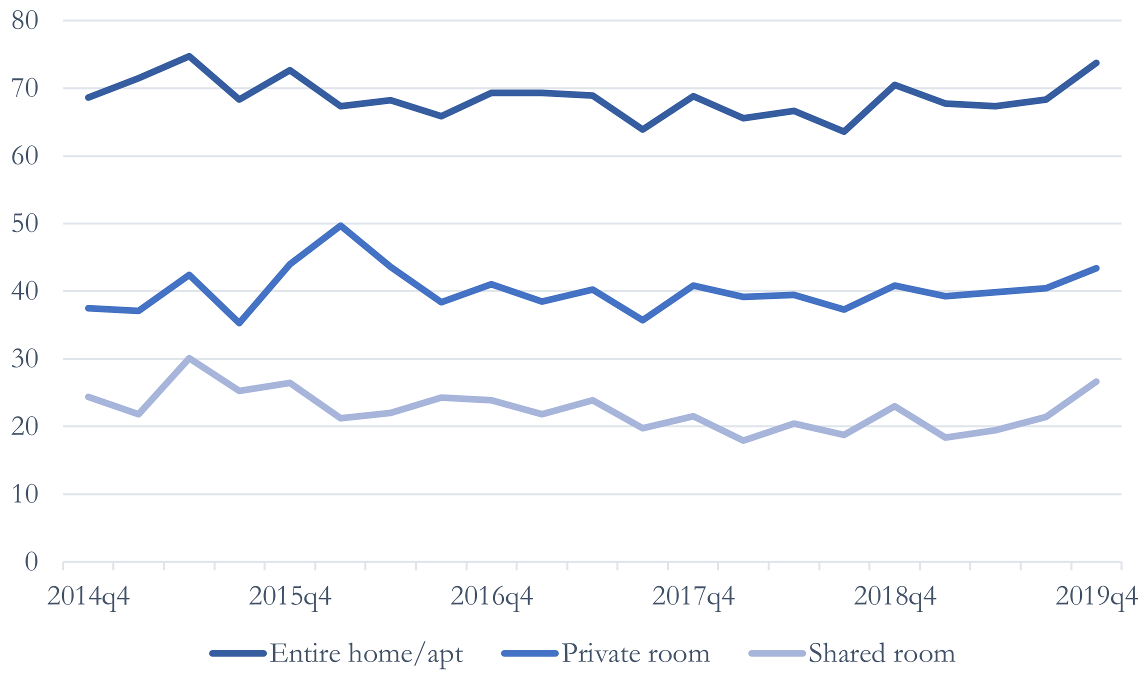

Figure 3.27. Averge revenue earned per booked night, by listing type. Only data for listings with occupancy rates greater than 1% has been used.

Clearly, entire homes are the most profitable, with nightly revenues ranging from €63 to €75. Unexpectedly, revenues per booked day have not increased since 2014, perhaps due to the excess of supply described in 3.3.3.

The last consideration regarding revenues stems from the distinction between single property and commercial hosts. Figure *3.28* shows how revenues for commercial hosts are typically higher, a predictable result if we think of commercial hosts as more organized, shrewd and experienced when it comes to advertising their listings.

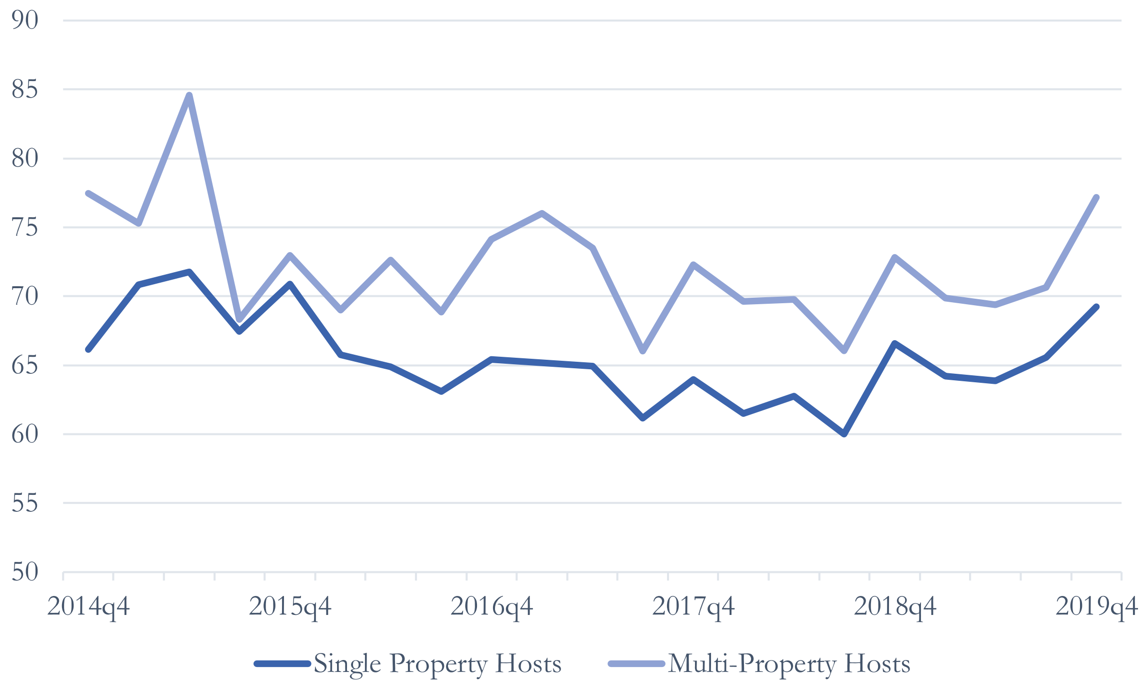

Figure 3.28. Average revenue earned per booked night for entire homes with occupancy rates above 1%. Quarterly data grouped by host category.

3.4 Idealista Analysis

Data provided by Idealista contain quarterly values of posted rents and selling prices for the neighbourhood identified by the platform. Unfortunately, the dataset provided is incomplete, as a neighbourhood is missing (it should be on the bottom right of the map). Using the housing stock composition provided by OMI, it has been calculated that about 11.000 properties are found in this area, less than 2,2% of the total stock. Nothing can be done to estimate these values so the entire area will be ignored.

Figure *3.29* and Figure *3.30* present heat maps regarding the average sale and rent prices in the first quarter of 2020 for each neighbourhood, respectively. Both values tend to be higher in central areas, even if the range of posted selling prices is much wider (in relative terms) than the one of asked rents. Moreover, high selling prices are concentrated in a few neighbourhoods, while high rents are found in more sections of the map; the second map is in fact darker than the first.

The evolution of house prices and rents for each Idealista neighbourhood is shown in Exhibit 4 and Exhibit 5, respectively.

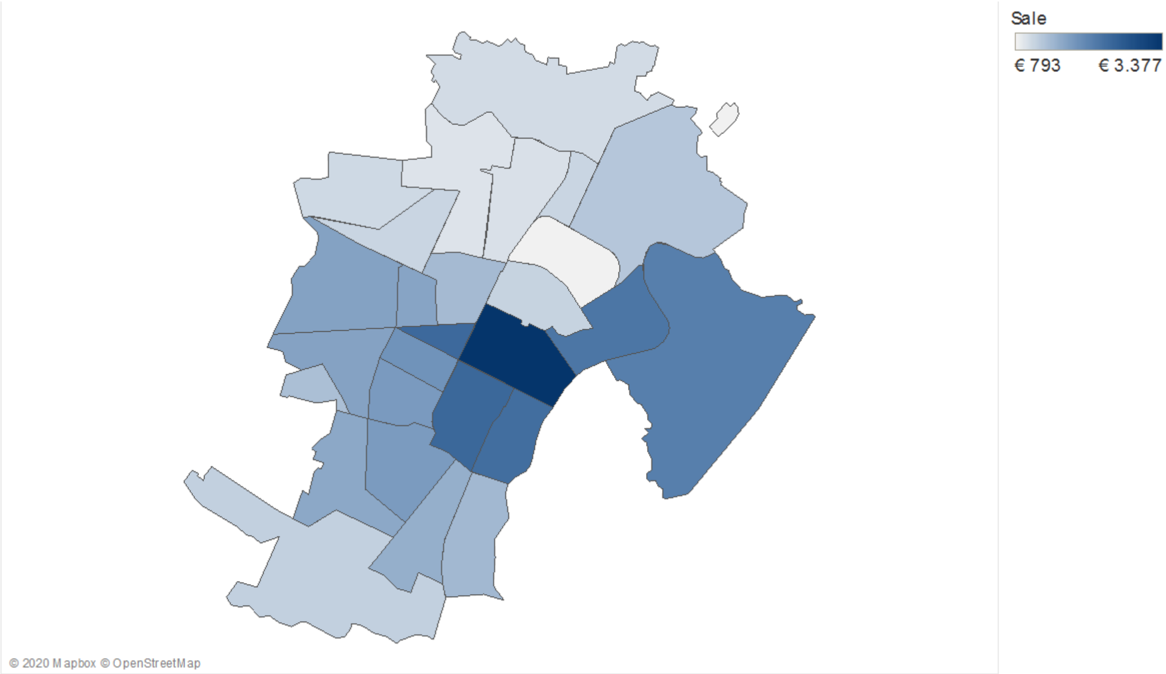

Figure 3.29. Average posted sale price for homes in the first quarter of 2020 in Turin.

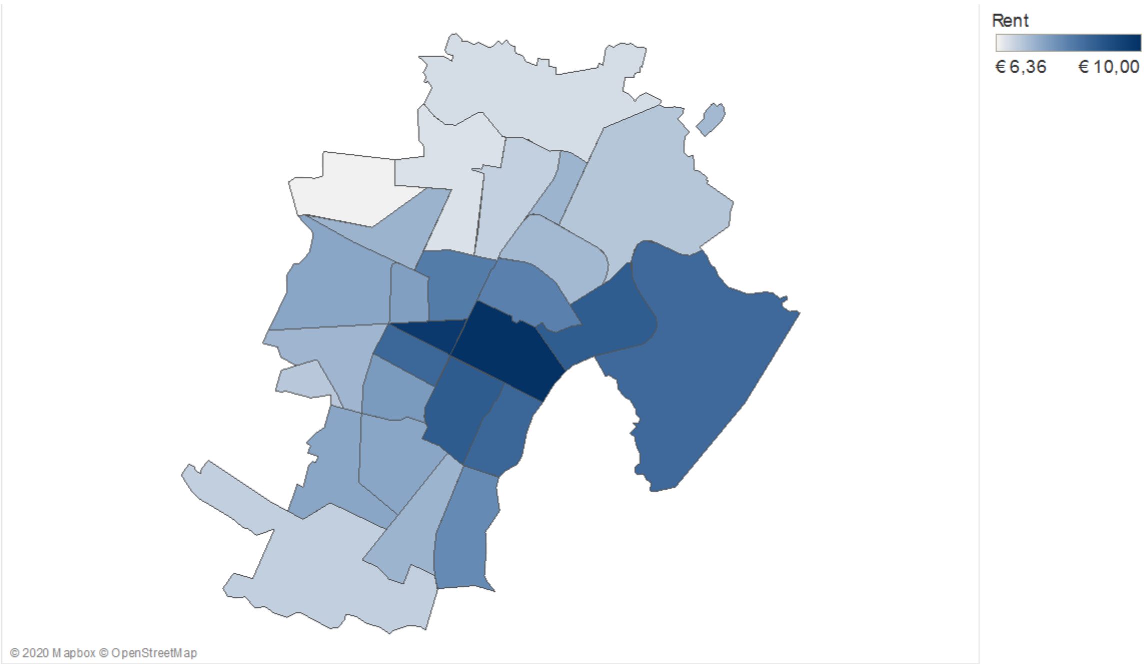

Figure 3.30. Average requested rent posted in the first quarter of 2020 in Turin.

Using the values provided by Idealista, and weighing them using the number of housing units in each neighbourhood provided by OMI, it is possible to estimate the average selling and renting prices for the city of Turin from 2012 to 2020. As the graph in Figure *3.31* shows, average selling prices have steadily decreased, from approximately 2.400 €/m² in the first quarter of 2012, to a little less of 1.700 €/m² at the beginning of 2018. From then on, only small fluctuations have occurred. A 30% drop in home prices is certainly steep, but not as dramatic as the bursts of real estate bubbles that took place during the 2008 financial crisis, mainly because this decline occurred during a time span of several years. Moreover, this trend is in line with the general trend of Italian property prices described in 1.3.

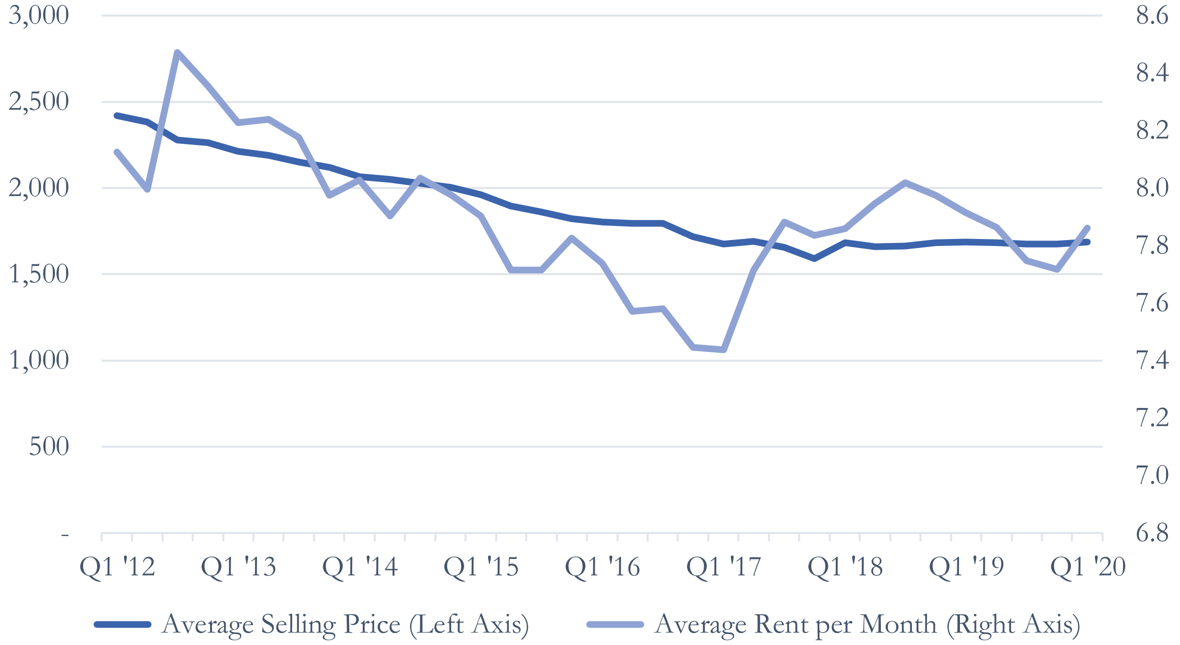

Figure 3.31. Weighted average selling price (left axis) and requested rent (right axis) in Turin, quarterly data provided by Idealista weighted on the basis of housing units reported by OMI.

Rent prices, on the other hand, have been more dynamic during the same period. Starting from an average of 8,13 €/m² per month in 2012, ups and downs have led to a low of 7,44 €/m² at the beginning of 2016. From then on, the average rent has risen to approximately 7,80 €/m². Considering that the average home in Turin is 91 m², these figures translate into an average rent of 715 €/month and average home values of 153.300 € in the first months of 2020. Once again, it is worth mentioning that these are posted prices, which usually differ from the ones the counterparties agree on.

City-wide average prices are a good way to grasp general trends, but neighbourhood-specific price variations offer precious insights on the different situations across the city. Assuming that the number of properties posted on Idealista does not vary significantly from quarter to quarter, the values used to calculate the percentages in the map have been identified in the following way:

- *Initial Value*: the average price posted in the first 4 quarters of 2012.
- *Final Value*: the average between the prices posted in the first quarter of 2020 and in the last 3 quarters of 2019.

Using values from the very first quarters of 2012 and 2020 would have been the fastest approach, but it would have been subject to the influence of outliers. The same could have happened if only 2 quarters per period were taken into account (posted prices present a sort of seasonality on some occasions), so a full year has been used. The same approach has been adopted for both rents and selling prices.

Changes in selling prices are shown in Figure *3.32*, where red areas stand for large losses and green sections for smaller ones. As one would expect, some areas have suffered sharper losses, at times halving the value of properties from the start of the period, while others (central neighbourhoods in particular) have only lost 20-30% of their value. A remarkable exception is the neighbourhood *Centro Storico*, where posted prices have only decreased by roughly 4%, while the second lowest contraction took place in *Cit Turin* (-14,72%).

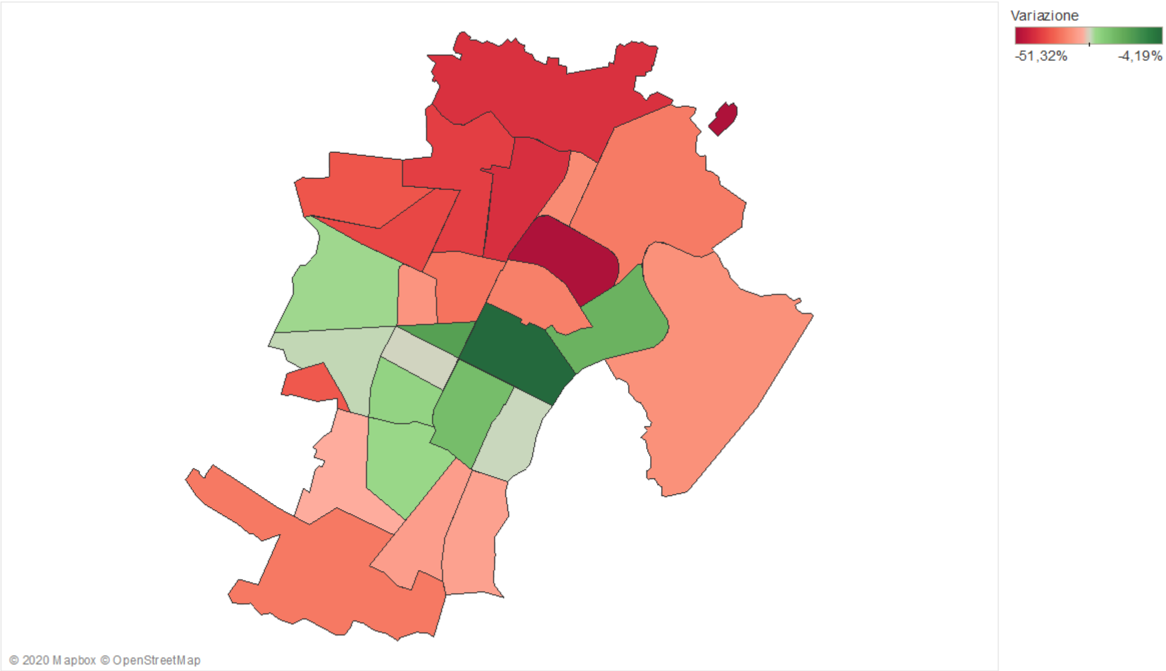

Figure 3.32. Heat map showing the variation of posted selling prices from 2012 to 2020 in Turin. Source: Idealista.

Figure *3.33* shows the same type of variation but for rents; the difference in this case is that some areas have experimented rent increments while others have not. Overall, the range of variation is smaller than the one registered with sales, since changes range from -13,32% to +9,66%, with central areas once again less negatively affected (light red corresponds to approximately -5%). The three neighbourhoods in the northernmost part of the city are an exception, since their average requested rents, already among the lowest in the city, have had obtained small gains.

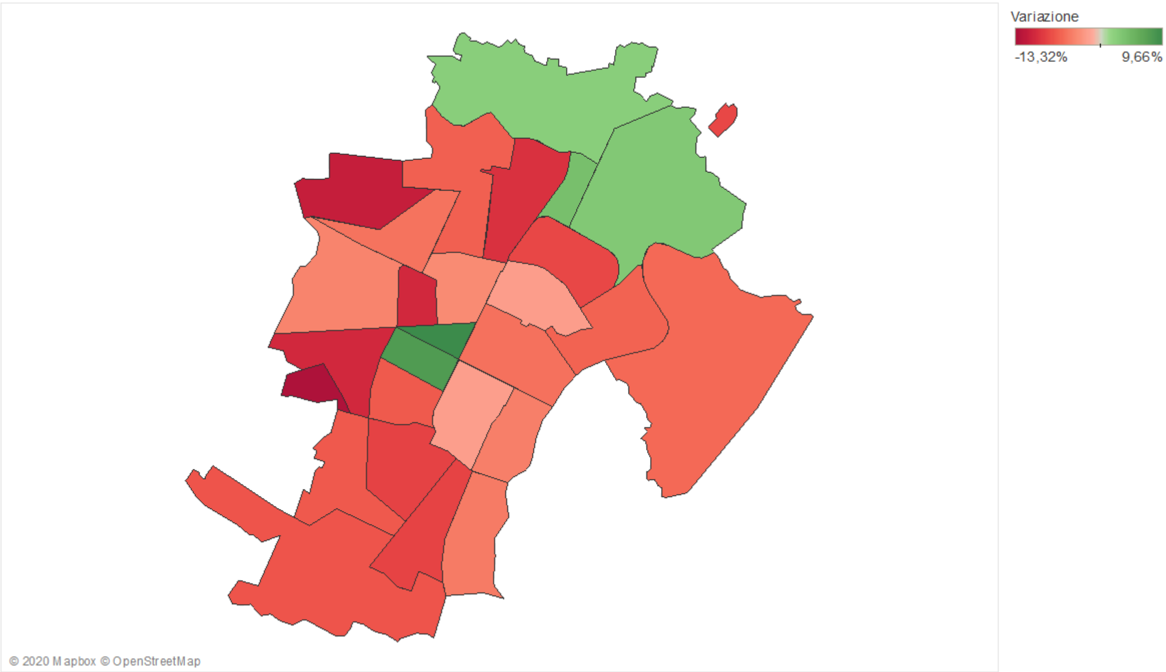

Figure 3.33. Heat map showing the variation of asked rent prices from 2012 to 2020 in Turin. Source: Idealista.

3.5 Consistency of data from OMI and Idealista

Now that prices from both OMI and Idealista are available, it is possible to investigate whether they present substantial differences or not. As the graph in Figure *3.34* shows, the average selling prices per square meter found for each semester essentially present the same trend for both OMI and Idealista. However, data provided by OMI has a discontinuous trend, while the line plotting Idealista prices is smoother. Specifically, the two measures are mostly corresponding, but in the first 4 semesters the differences are significant.

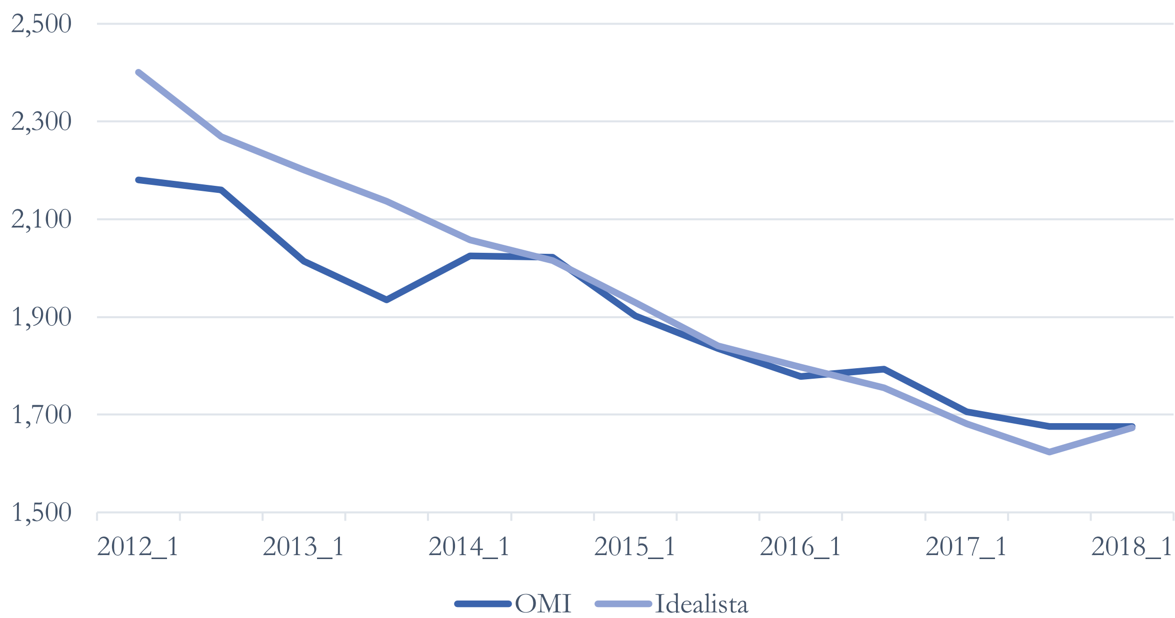

Figure 3.34. Average sale price per semester (€/m²).

With Stata, it is possible to perform a statistical t-test to see whether the values found for OMI can be considered the same as the ones found for Idealista. To do so, a new variable was created (*sale-diff*[17]) to test the null hypothesis of it being equal to 0. The resulting output, calculated with a 95% confidence interval, is the following:

One-sample t test for sale_diff

	obs	Mean	St Err	t value	p value
Sale_diff	351	-11.021	11.945	-.922	.357

The test is unable to reject the null hypothesis, thus the two prices found for each semester cannot be considered significantly different.

Figure *3.35* reports a graph similar to the previous one, but for monthly rent prices. In this case, the differences between OMI and Idealista are considerable for almost every semester, with few exceptions. The presence of these inconsistencies was predicted in 3.1.2, where they have been described as the result of an incentive for home-owners to under report their rental incomes.

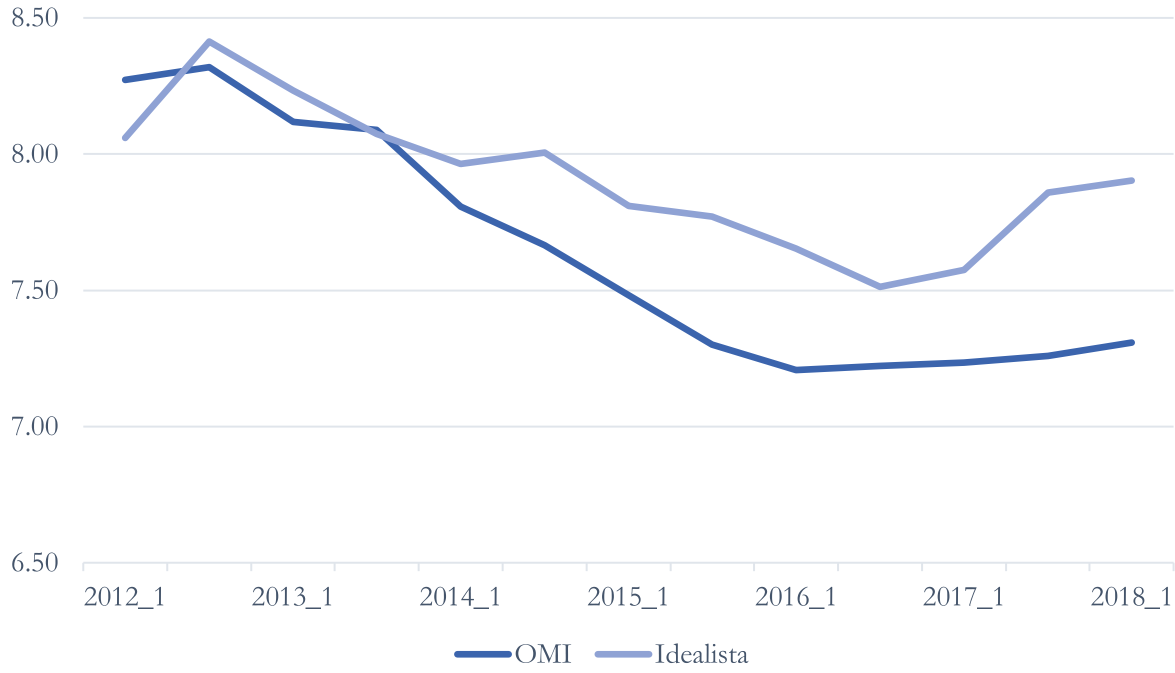

Figure 3.35. Average monthly rent price per semester (€/m^2).

[17] Calculated as: *Sale_diff* = OMI_sale – Idealista_sale. OMI_sale and Idealista_sale are the average selling prices registered for each neighbourhood in every semester using data from OMI and Idealista, respectively.

To investigate whether the differences are statistically significant, the variable *rent_diff*[18] was created. Performing a t-test, the following results are found:

One-sample t-test for rent_diff

	obs	Mean	St Err	t value	p value
rent diff	351	-.278	.029	-9.805	0

The null hypothesis, which consisted in *rent_diff* being equal to 0, has to be rejected and the two measures (OMI_rent and Idealista_rent) cannot be considered the same. This means that the initial intuition regarding the effect of under reporting (or other elements that may have an impact) is correct. Hence, it is not possible to switch between the two data sources and it is advisable to perform separate analyses for both.

[18] Calculated as: *Rent_diff* = OMI_rent – Idealista_rent.

Chapter 4

Econometric Model

This chapter introduces and describes the econometric analyses that have been conducted on the datasets presented thus far. Starting from the descriptive statistics, the following sections cover the three main groups of analyses that have been run: on revenues, on rents, and on selling prices.

4.1 Descriptive Statistics

This section presents the main descriptive statistics for the variables used in the econometric models presented in this chapter. Some of these variables belong to the datasets described in Chapter 3, while the rest have been taken from other sources that have been merged with the original.

4.1.1 Listing Characteristics

The first variables to look at describe a listing's characteristics. After having seen the number of listings by listing type and their evolution over the years, Table 6 presents statistics on the number of bedrooms and on the number of bathrooms found across the city in a given quarter.

	Number of Bedrooms			Number of Bathrooms		
Year Quarter	**Mean**	**Median**	**Variance**	**Mean**	**Median**	**Variance**
2014q4	1,26	1	0,46	1,15	1	0,19
2015q1	1,27	1	0,50	1,15	1	0,18
2015q2	1,25	1	0,49	1,14	1	0,17
2015q3	1,22	1	0,46	1,14	1	0,17
2015q4	1,20	1	0,45	1,14	1	0,16
2016q1	1,19	1	0,43	1,13	1	0,15
2016q2	1,19	1	0,45	1,14	1	0,17
2016q3	1,20	1	0,45	1,13	1	0,17
2016q4	1,19	1	0,43	1,13	1	0,17
2017q1	1,20	1	0,42	1,13	1	0,17
2017q2	1,20	1	0,42	1,13	1	0,17
2017q3	1,20	1	0,43	1,13	1	0,17
2017q4	1,20	1	0,43	1,13	1	0,17
2018q1	1,20	1	0,43	1,13	1	0,17
2018q2	1,20	1	0,47	1,13	1	0,20
2018q3	1,20	1	0,48	1,13	1	0,21
2018q4	1,20	1	0,48	1,14	1	0,21
2019q1	1,20	1	0,47	1,13	1	0,20
2019q2	1,20	1	0,48	1,13	1	0,20
2019q3	1,20	1	0,42	1,14	1	0,17
2019q4	1,20	1	0,43	1,14	1	0,19

Table 6. Descriptive statistics – Number of bedrooms, Number of bathrooms.

The table shows that the median value for both attributes was 1, while the average number of rooms per listing averaged 1,2 in most quarters, and the average number of bathrooms varied between 1,13 and 1,15. Variance is low for both variables, meaning that listings with a high number of rooms are very rare. These variables are going to be included in the analysis exploring the variables that directly impact the revenues of a listing, since it is reasonable to expect that a higher number of rooms is associated with more guests and, as a consequence, to more revenues.

Another important variable when looking at a listing is the minimum stay required by the host to finalize a booking. If a listing has a minimum stay of 3 days, it means that guests have to book it for a minimum of 3 days, otherwise the host will not accept the booking. Since the focus of Airbnb is on short-term contracts, the expectation is to find an average minimum stay that only requires a few days' bookings.

Minimum Stay			
Year Quarter	**Mean**	**Median**	**90th Percentile**
2014q4	3,29	2	3
2015q1	3,14	2	3
2015q2	3,14	2	3
2015q3	2,99	2	3
2015q4	2,94	2	3
2016q1	2,82	2	3
2016q2	2,80	2	3
2016q3	2,70	2	3
2016q4	2,57	2	3
2017q1	2,62	2	3
2017q2	2,86	2	3
2017q3	2,89	2	3
2017q4	2,89	2	3
2018q1	2,96	2	3
2018q2	2,92	2	3
2018q3	2,89	2	3
2018q4	2,93	2	3
2019q1	2,94	2	3
2019q2	3,10	2	3
2019q3	3,11	2	3
2019q4	3,10	2	3

Table 7. Descriptive statistics – Minimum stay.

Table 7 shows that the average minimum stay has slightly changed over the years, but always around the 3-night value. However, the median stay has always been of 2 nights, with 90% of listings having a minimum stay of 3 or less nights. This means that the majority of listings are rented out for occasional stays, and that hosts are not using Airbnb to find long-term tenants, which is in line with the value proposition of the platform and the above considerations.

To take into account the quality of a listing, it is useful to include the rating given by past guests to single properties. To do so, it is possible to use the variable overall rating, which takes into account all the reviews given by guests since the listing has been online. Table 8 shows that, on average, the overall rating obtained across the city is very high, since only the bottom 10% of listings have had a rating lower than 4 out of 5 in some of the quarters for which data is available. The median rating was found to be either 4,7 or 4,8 depending on the quarter, which is a high value and shows either satisfaction from guests, care from hosts, or both.

Overall Rating

Year Quarter	10th Percentile	Mean	Median	90th Percentile
2014q4	4	4,60	4,7	5
2015q1	4	4,60	4,7	5
2015q2	4	4,59	4,7	5
2015q3	4	4,59	4,7	5
2015q4	4	4,58	4,7	5
2016q1	4	4,59	4,7	5
2016q2	4	4,59	4,7	5
2016q3	4	4,60	4,7	5
2016q4	4	4,61	4,7	5
2017q1	4	4,61	4,7	5
2017q2	4	4,62	4,7	5
2017q3	4	4,62	4,8	5
2017q4	4,1	4,64	4,8	5
2018q1	4,2	4,64	4,8	5
2018q2	4,2	4,64	4,8	5
2018q3	4,2	4,64	4,8	5
2018q4	4,2	4,65	4,8	5
2019q1	4,2	4,65	4,8	5
2019q2	4,2	4,66	4,8	5
2019q3	4,2	4,66	4,8	5
2019q4	4,2	4,68	4,8	5

Table 8. Descriptive statistics – Overall rating.

4.1.2 Neighbourhood Characteristics

To take into account the differences stemming from the location of listings, variables describing neighbourhood characteristics have been used as well. To start with, data regarding the hotel industry in Turin has been gathered for each area, considering the number of hotel rooms as well as their average number of stars. To have a more meaningful result, the average number of stars has been weighted against the number of rooms for each hotel.

Neighbourhood	Number of Hotel Rooms	Weighted Average Number of Stars
Centro Storico	2111	3,60
San Salvario	703	1,82
Crocetta	658	3,34
Nizza-Millefonti	586	3,79
Regio Parco-Barca-Bertolla	296	2,64
Aurora	285	1,15
Barriera di Milano	209	1,93
Madonna di Campagna	182	4,23
Mirafiori Nord	165	2,61
Cit Turin	156	2,04
Mirafiori Sud	144	1
Pozzo Strada	144	2,81
Lingotto	141	1
San Paolo	95	2
San Donato	87	1
Sassi-Madonna del Pilone	80	2,05
Cenisia	58	1
Parella	32	1,88
Campidoglio	28	3
Falchera-Villaretto	24	1
Lucento	20	1
Borgata Lesna	0	0
Borgo Vittoria	0	0
Rebaudengo	0	0
Santa Rita	0	0
Vallette	0	0
Vanchiglia	0	0

Table 9. Descriptive statistics – Number of hotel rooms, Average number of stars

Unsurprisingly, given their central location, neighbourhoods such as *Centro Storico*, *Crocetta* and *San Salvario* have the highest number of hotel rooms in the city. On the other hand, the average number of stars doesn't follow the same logic, since less-central neighbourhoods (*Madonna di Campagna* for example) are also found to have high ratings. This is due to some large hotels primarily used by business travellers, which are often located in less-central neighbourhoods where there is more available space and it is easier to arrive by car.

Other important variables to consider when looking at neighbourhood characteristics are listed in Table 10. The first column shows the percentage of occupied homes out of the housing stock, which range from a minimum of 85,2% in neighbourhood *Sassi-Madonna del Pilone*, to a maximum of 97,1% in *Vallette*. The second column is the share of vacant homes and has been calculated as the difference between 100% and the share of occupied homes. The third column shows the percentage of families living in a rented home; values vary a lot across neighbourhoods, with a maximum of 42,1% of families living in a rented home in *Vallette*, to a minimum of 21,6% in *Mirafiori Nord*. The last column refers to the type of buildings, reporting the percentage of commercial buildings found in each neighbourhood.

Neighbourhood	**Occupied Homes**	**Vacant Homes**	**Families Living in a rented home**	**Share of Commercial Buildings**
Centro Storico	0,862	0,138	0,318	0,341
Aurora	0,865	0,135	0,320	0,413
Barriera di Milano	0,910	0,090	0,327	0,386
Borgata Lesna	0,897	0,103	0,321	0,517
Borgo Vittoria	0,940	0,060	0,294	0,456
Campidoglio	0,908	0,092	0,332	0,384
Cenisia	0,876	0,124	0,331	0,376
Cit Turin	0,885	0,115	0,295	0,408
Crocetta	0,875	0,125	0,299	0,420
Falchera-Villaretto	0,943	0,057	0,271	0,373
Lingotto	0,959	0,041	0,256	0,425
Lucento	0,958	0,042	0,274	0,430
Madonna di Campagna	0,940	0,060	0,272	0,458
Mirafiori Nord	0,967	0,033	0,216	0,408
Mirafiori Sud	0,962	0,038	0,221	0,545
Nizza-Millefonti	0,926	0,074	0,263	0,491
Parella	0,922	0,078	0,277	0,412
Pozzo Strada	0,937	0,063	0,232	0,430
Rebaudengo	0,955	0,045	0,230	0,420
Regio Parco-Barca-Bertolla	0,910	0,090	0,340	0,459
San Donato	0,931	0,069	0,289	0,395
San Paolo	0,912	0,088	0,271	0,395
San Salvario	0,913	0,087	0,311	0,401
Santa Rita	0,934	0,066	0,254	0,408
Sassi-Madonna del Pilone	0,852	0,148	0,234	0,342
Vallette	0,971	0,029	0,421	0,460
Vanchiglia	0,924	0,076	0,284	0,472

Table 10. Descriptive statistics – Occupied homes, Vacant homes, Families living in a rented home, Share of commercial buildings.

4.2 Analysis on Revenues

This set of regressions is aimed at investigating the relationship between the total revenues of a listing and its characteristics. The Airbnb dataset has been enriched with datapoints including the number of hotel rooms in a given neighbourhood, the average number of 'stars' for these hotels, and dummy variables to control for other aspects. Two groups of regressions have been performed, the first without neighbourhood fixed-effects, and the second involving them.

4.2.1 Regression Results

The dependent variable used to obtain the results is the natural logarithm of quarterly revenues (*Log(Revenues)*) for a listing. The analysis was run using the *reghdfe* command on Stata, to be able to exploit the longitudinal nature of the dataset as well as to apply fixed-effects. As Table 12 shows, 3 different regressions have been performed, starting from a baseline model that only contains variables belonging to the listing's characteristics.

The first column presents the coefficients found for the specification containing listing-specific variables only, while in the second column neighbourhood characteristics are added. These new variables provide information on the number of hotels, rent and home prices, and Airbnb density. In the third column the variables do not change, but the specification includes fixed-effects at 'band level', which means that neighbourhoods are sorted among the different area groups described in 3.1.2. by adding the *absorb(fascia)* option to the command. By comparing the boundaries of Idealista and OMI maps, it is possible to assign each Idealista neighbourhood to an OMI area group (*fascia*). However, since the neighbourhood *Centro Storico* is the only one belonging to the 'Central' area group, it was decided to consider it as 'Semi-Central' to avoid any issues that may arise when only one neighbourhood is assigned to an area group. All three specifications include time fixed-effects at year-quarter level.

Specifically, the estimated equations are the following:

(1) $$log(Y_{it}) = \alpha + \beta X_{it} + \tau_t + \varepsilon_{it}$$

(2) $$log(Y_{it}) = \alpha + \beta X_{it} + \gamma W_{jt} + \tau_t + \varepsilon_{it}$$

(3) $$log(Y_{it}) = \alpha + \beta X_{it} + \gamma W_{jt} + K_k + \tau_t + \varepsilon_{it}$$

Y_{it} : total amount of revenues generated by listing i in quarter t

X_i : listing-specific characteristics

W_{jt} : neighbourhood-specific time-varying characteristics

K_k : band-level fixed-effects

τ_t : time fixed-effects for quarter t

The groups of variables used in the model are listed and described in the following table (Table 11):

Log(ReservationDays) Log(AverageReservationLength) # of Photos # of Bedrooms # of Bathrooms Overall Rating Log(MinimumStay) Log(NumberOfReviews)	Listing-specific data describing characteristics and popularity on the platform
Airbnb Superhost (dummy) Commercial Listing (dummy) Entire home (dummy)	Dummies describing host, listing and neighbourhood type
Log(NumberOfHotelRooms) Average # of Stars	These variables describe the dimensions and the type of accommodations that can be found in neighbourhood *n*
Log(Density)	Airbnb density is a value ranging from 0 to 1 representing the percentage of the housing stock in neighbourhood *n* that is listed on Airbnb in quarter *t*
Log(Rent) Log(Sale)	Quarterly neighbourhood values taken from Idealista

Table 11. Variables used for the regression on revenues.

Output results:

Dependent Variable: **Log(Revenue)**	(1) Property Characteristics	(2) Neighbourhood Characteristics	(3) Neighbourhood Band Fixed-Effects
Log(ReservationDays)	1.734***	1.729***	1.729***
	(0.0155)	(0.0135)	(0.0135)
Log(AverageReservationLength)	0.507***	0.519***	0.519***
	(0.0201)	(0.0243)	(0.0244)
Number of Photos	0.00633***	0.00590***	0.00589***
	(0.000895)	(0.000867)	(0.000862)
Bedrooms	0.157***	0.169***	0.169***
	(0.0196)	(0.0203)	(0.0202)
Bathrooms	0.145***	0.134***	0.135***
	(0.0284)	(0.0265)	(0.0264)
Overall Rating	0.0823***	0.0713***	0.0712***
	(0.0292)	(0.0248)	(0.0247)
Log(MinimumStay)	-0.129***	-0.129***	-0.129***

	(0.0187)	(0.0177)	(0.0176)
Log(NumberofReviews)	-0.0650***	-0.0659***	-0.0661***
	(0.0115)	(0.0116)	(0.0116)
Airbnb Superhost (dummy)	0.0275	0.0267	0.0271
	(0.0237)	(0.0233)	(0.0234)
Commercial Listing (dummy)	0.254***	0.249***	0.249***
	(0.0245)	(0.0215)	(0.0215)
Entire Home (dummy)	0.353***	0.331***	0.331***
	(0.0140)	(0.0177)	(0.0178)
Log(NumberOfHotelRooms)		-0.0154	-0.0129
		(0.0137)	(0.0143)
Average # of Stars		0.0432	0.0354
		(0.0290)	(0.0306)
Log(Density)		0.0663	0.0732
		(0.0449)	(0.0479)
Log(Rent)		-0.0211	0.0867
		(0.363)	(0.354)
Log(Sale)		0.0852	0.0802
		(0.0519)	(0.0498)
Constant	-0.0157	-0.196	-0.349
	(0.139)	(0.957)	(0.968)
Observations	77,230	77,230	77,230
R-squared	0.899	0.900	0.900
Year-quarter FE	YES	YES	YES
Neighbourhood Band FE			YES

Robust standard errors in parentheses

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

Table 12. Stata output - Revenues regression.

The results show that a listing's revenues are positively correlated with the number of reservation days and the average length of the reservation. Unsurprisingly, a 1% in reservation days leads to an estimated 1,7% increase in revenues, while average stays have a lighter impact, since a 1% increase in the average stay roughly translates into a 0,5% increment for revenues. In the first column, it is possible to see that also the number of bedrooms and the number of bathrooms allow for higher revenues, since higher values indicate larger homes and, as a consequence, more guests. The number of photos is also positively correlated, but its effect is small, since an additional photo approximately leads to a 0,6% increase in revenues.

The overall rating assigned by past guests to the listing is also positively correlated with revenues, and it is possible to identify two main reasons for this. First, a customer which is uncertain between two listings with similar characteristics is more likely to choose the one with a higher rating, which inevitably translates into more customers and higher fill rates on the long term. Second, higher ratings may stem from better curated listings, for which the owners may pretend more money. The coefficient regarding the minimum stay is negatively correlated, which is reasonable if one thinks about the typical Airbnb user, which is renting a home for a short period of time. Therefore, longer minimum stays are a disincentive and lead to lower bookings.

Among the dummy variables, only the ones referring to commercial listings and entire homes are statistically significant. Both characteristics have a positive impact on revenues, with entire homes leading to a 33,1% increase in revenues (when looking at results in the third column). This finding is in line with the data shown in Figure *3.27*, where daily revenues for entire homes were found twice as profitable as the ones for private rooms. Owning a commercial listing is also more profitable, and this is because these listings are listed on the platform for a larger amount of time, and also because owners with more than one listing are expected to be more committed in providing timely responses to potential guests.

Focusing on the second specification, the variables describing neighbourhood characteristics are not significant, and the same holds true when introducing fixed-effects. However, only small changes occur from one specification to the other, meaning that the interpretations previously provided are still valid. Overall, the R-squared for the third column indicates that 90% of the variability is explained by the model, which can be considered a very good result.

4.3 Analysis on Rents

Once the analysis on which variables impact the revenues of a given listing has been performed, it is possible to aggregate listings data at neighbourhood level to investigate the relationship between Airbnb activity and the evolution of rents. Two different regressions have been built, the first using data from Idealista, the second using the OMI dataset.

4.3.1 Regression results using rent data from Idealista

In this case the dependent variable is *Log(Rent)*, which refers to the quarterly average of rents posted on Idealista's website for a specific neighbourhood, while the other variables used in the model are described in Table 13. Starting from a baseline regression, OMI area controls are subsequently added to take into account changes in neighbourhood characteristics. Area group fixed-effects have been added in the last column of Table 14, while year-quarter fixed-effects are included throughout the specifications. The variable of interest is *Log(Density)*, which is a proxy of Airbnb activity in a given neighbourhood and quarter.

The estimated equations are the following:

(1) $$log(Y_{it}) = \alpha + \beta\, log(Density_{it}) + \gamma X_{it} + \tau_t + \varepsilon_{it}$$

(2) $$log(Y_{it}) = \alpha + \beta\, log(Density_{it}) + \gamma X_i + \delta W_{it} + \tau_t + \varepsilon_{it}$$

(3) $$log(Y_{it}) = \alpha + \beta\, log(Density_{it}) + \gamma X_i + \delta W_{it} + K_k + \tau_t + \varepsilon_{it}$$

Y_{it} : the average rent posted on Idealista for neighbourhood *i* in quarter *t*
$Density_{it}$: Airbnb density for neighbourhood *i* in quarter *t*
X_i : baseline characteristics
W_{it} : neighbourhood-specific time-varying characteristics
K_k : band-level fixed-effects
τ_t : time fixed-effects for quarter *t*

Log(Density)	A value ranging from 0 to 1 representing the percentage of the housing stock in neighbourhood *n* that is listed on Airbnb in quarter *t*
Log(NumberOfHotelRooms) Average # of Stars	These variables describe the dimensions and the type of accommodations that can be found in neighbourhood *n*
Log(HomesDensity) Log(ShopsDensity) Log(OccupiedHomes) Log(RentingFamilies) Log(CommercialBuildings)	This group of variables includes statistics on the composition of buildings and residents in neighbourhood *n* in quarter *t*

Table 13. Variables used for the regression on rent prices.

Dependent Variable: **Log(Rent)**	(1) Baseline	(2) Neighbourhood Characteristics	(3) Neighbourhood Band Fixed-Effects
Log(Density)	0.0876***	0.0656***	0.0561***
	(0.0123)	(0.0102)	(0.00848)
Log(NumberOfHotelRooms)	0.00582	-0.000272	-0.00464
	(0.00914)	(0.00785)	(0.00574)
Average # of Stars	-0.00313	-0.00697	0.00520
	(0.0140)	(0.0120)	(0.00872)
Log(HomesDensity)		-0.101	-0.0702
		(0.0791)	(0.0768)

Log(ShopsDensity)		0.122	0.0775
		(0.0756)	(0.0775)
Log(OccupiedHomes)		-0.510	-0.430
		(0.429)	(0.388)
Log(RentingFamilies)		-0.187***	-0.196***
		(0.0608)	(0.0493)
Log(CommercialBuildings)		0.0540	0.0492
		(0.0654)	(0.0671)
Constant	2.654***	2.643***	2.406***
	(0.0945)	(0.134)	(0.180)
Observations	567	567	567
R-squared	0.673	0.772	0.796
Year-quarter FE	YES	YES	YES
Neighbourhood Band FE			YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14. Stata output – Rent price regression using data from Idealista.

From the output table above, it is possible to see a positive correlation between the rise of Airbnb listings and rent prices. In the first column, the predicted effect is 0,00876, meaning that a 1% increase in Airbnb listings directly translates to a 0,0876% increase in rents. However, when neighbourhood characteristics and fixed-effects are taken into account, the entity of this effect is redefined, and a coefficient of 0,0561, which estimates a 0,0561% increase, is found. The reason for this is that other factors determine rent prices in neighbourhoods, and specific controls have been included in columns 2 and 3 to take them into account. Among these factors, the only variable found to be significant is *Log(RentingFamilies)*, which represents the percentage of families renting the home they live in. The correlation with rent prices is estimated to be negative, meaning that a 1% increase in the number of renting families leads to a 0,196% decrease in rents. To provide an interpretation for this finding, it is necessary to consider the habits of Italian households, which tend to own the houses they live in. Therefore, lower ownership rates are usually found in poorer neighbourhoods or in areas where there are large social housing developments. Although the remaining control variables have no statistical significance, the overall R-squared, at 0,796, can be considered a good result.

4.3.2 Regression results using rent data from OMI

The following regression uses OMI rent data which, unlike Idealista's, are not available for every quarter, but for semesters only. This changes the datasets and strongly reduces the number of observations used for the analysis. The variables included in the model are the same as the ones listed in Table 13, except for the fact that they have now been transformed from quarterly to semester level data, adjusting the new values by averaging and summing the previous quarterly values. Apart from these changes, the estimated equations are identical to the ones presented in 4.3.1.

Results are reported in the following table (Table 15):

Dependent Variable: **Log(OMI_Rent)**	(1) Baseline	(2) Neighbourhood Characteristics	(3) Neighbourhood Band Fixed-Effects
Log(Density)	0.0701***	0.0473***	0.0387**
	(0.0167)	(0.0135)	(0.0144)
Log(NumberOfHotelRooms)	0.00156	-0.00565	-0.00925
	(0.0136)	(0.0125)	(0.0114)
Average # of Stars	0.00825	0.00668	0.0167
	(0.0246)	(0.0220)	(0.0197)
Log(HomesDensity)		-0.189	-0.164
		(0.114)	(0.115)
Log(ShopsDensity)		0.211*	0.175
		(0.108)	(0.113)
Log(OccupiedHomes)		0.423	0.488
		(0.675)	(0.645)
Log(RentingFamilies)		-0.136*	-0.142**
		(0.0738)	(0.0661)
Log(CommercialBuildings)		0.0206	0.0144
		(0.0936)	(0.0961)
Constant	2.428***	2.713***	2.518***
	(0.125)	(0.166)	(0.249)
Observations	189	189	189
R-squared	0.543	0.664	0.684
Year-semester FE	YES	YES	YES
Neighbourhood Band FE			YES

Robust standard errors in parentheses

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

Table 15. Stata output – Rent price regression using data from OMI.

These results are very similar to the ones shown in Table 14, but the R-squared is lower in each of the specifications. However, it is possible to see that Airbnb density is still positively correlated with rent prices in each of the three columns, leading to a 0,0387% rise in rents whenever a 1% increase in density takes place and band fixed-effects are considered. The coefficient found with data from Idealista suggested a 0,0561% increase, which is slightly different but similar enough to accept both values. Similarly, also the share of families renting their homes is found to be significant, and negatively correlated.

Although results are similar, the R-squared is now lower than with Idealista data and, considering the differences highlighted in section 3.5 between the two datasets (OMI and Idealista), as well as their granularity in time (quarter values against semester data), the findings described in Table 14 are to be preferred.

4.4 Analysis on Home Prices

After having seen the relationship between rent prices and Airbnb, the last variable to look at is the average sale price for homes in a given neighbourhood. Similarly to what has been done in section 4.3, both Idealista and OMI datasets have been used to perform two distinct regressions, collapsing data at neighbourhood level in the same way.

4.4.1 Regression results using home prices from Idealista

The dependent variable is now *Log(Sale)*, where *Sale* represents the quarterly average price per square meter posted on Idealista. The other variables included in the model have already been described in Table 13. Starting from a baseline regression, OMI area controls and neighbourhood band fixed-effects are subsequently added to take into account changes in neighbourhood characteristics, while quarter fixed-effects have included throughout the analyses. As in 4.3, the variable of interest is *Log(Density)*, which is a proxy of Activity in a given neighbourhood and quarter. The estimated equations are the following:

$$(1) \qquad log(Y_{it}) = \alpha + \beta\, log(Density_{it}) + \gamma X_{it} + \tau_t + \varepsilon_{it}$$

$$(2) \qquad log(Y_{it}) = \alpha + \beta\, log(Density_{it}) + \gamma X_i + \delta W_{it} + \tau_t + \varepsilon_{it}$$

$$(3) \qquad log(Y_{it}) = \alpha + \beta\, log(Density_{it}) + \gamma X_i + \delta W_{it} + K_k + \tau_t + \varepsilon_{it}$$

Y_{it} : the average price per square meter asked on Idealista for neighbourhood *i* in quarter *t*
$Density_{it}$: Airbnb density for neighbourhood *i* in quarter *t*
X_i : baseline characteristics
W_{it} : neighbourhood-specific time-varying characteristics
K_k : band-level fixed-effects
τ_t : time fixed-effects for quarter *t*

The output is shown in the following table (Table 16).

Dependent Variable: **Log(Sale)**	(1) Baseline	(2) Neighbourhood Characteristics	(3) Neighbourhood Band Fixed-Effects
Log(Density)	0.194***	0.129**	0.111**
	(0.0428)	(0.0471)	(0.0479)
Log(NumberOfHotelRooms)	-0.0260	-0.0563	-0.0647
	(0.0357)	(0.0352)	(0.0386)
Average # of Stars	0.0776	0.0688	0.0921
	(0.0640)	(0.0547)	(0.0683)
Log(HomesDensity)		-0.515**	-0.456**
		(0.237)	(0.217)
Log(ShopsDensity)		0.558**	0.473**
		(0.224)	(0.214)
Log(OccupiedHomes)		-0.898	-0.745
		(1.762)	(1.812)
Log(RentingFamilies)		-0.895***	-0.913***
		(0.263)	(0.246)
Log(CommercialBuildings)		0.0178	0.00844
		(0.323)	(0.329)
Constant	8.871***	8.658***	8.205***
	(0.325)	(0.475)	(0.619)
Observations	567	567	567
R-squared	0.459	0.655	0.667
Year-quarter FE	YES	YES	YES
Neighbourhood Band FE			YES

Robust standard errors in parentheses

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

Table 16. Stata output – Regression on home prices using data from Idealista.

Starting from the first column, results show a strong positive correlation between Airbnb density and sale prices, where a 1% increase in density leads to a 0,194% increase in valuation for homes in the same neighbourhood. The R-squared is below 50% in this case, but the addition of variables describing neighbourhood characteristics allows it to reach 65,5% in the second column. Among these new variables, three of them are significant: homes density, shops density, and the percentage of renting families. Homes density presents a negative correlation with home prices, given that a 1% increase in homes density leads to approximately a 0,515% decrease in prices. Clearly, a high homes density is associated with large buildings mostly made up of apartments and usually found in less-central neighbourhoods. Shops density, on the other hand, positively impacts home prices by 0,558% for every 1% increase in density. This result is easy to understand, given that neighbourhoods with a higher shops density have more comforts, are more interesting and add value to homes located in the area. The variable describing the share of families renting their homes is once again found to be statistically significant and negatively correlated with the dependent variable, so the explanation given in 4.3.1 still holds true.

The inclusion of band fixed effects slightly alters the results described above, but the statistically significant variables do not change. From the new coefficients, it is possible to estimate that a 1% increase in Airbnb listings, on a fixed stock of homes in the neighbourhood, leads to a 0,111% increase in home values. This finding is extremely important because it shows that Airbnb presence has an impact on home prices. The interpretation of this can be twofold. First, a higher Airbnb density means that a higher share of homes is taken off the real estate market, causing a drop in supply and subsequent price increases. However, the population in Turin is ageing and declining rather than booming, therefore it is unlikely that a similar effect is driven by a change in supply. The second, and more likely, interpretation is that home prices have risen (or declined more slowly depending on the neighbourhood considered) because potential owners are now offered an alternative income stream, the entity of which is enhanced by a macroeconomic context where low interest rates have depressed income from capital alongside the cost of borrowing. This lower cost, coupled with the nimble business opportunities provided by Airbnb, means that it is easier for a small investor to buy a house in order to achieve a fairly stable, and remunerative, source of income. The natural consequence is a higher valuation of the asset which, in this case, is represented by the average sale price per square meter.

4.4.2 Regression results using home prices from OMI

This section is dedicated to the same analysis conducted above, but uses data from OMI instead. Once again, the data is available at semester-level only, therefore some adjustments have been made to use a coherent time horizon. The variables are the same ones already presented, except for *Log(Sale)* which is now OMI-based.

The output is shown in Table 17.

Dependent Variable: **Log(OMI_Sale)**	(1) Baseline	(2) Neighbourhood Characteristics	(3) Neighbourhood Band Fixed-Effects
Log(Density)	0.137***	0.0758**	0.0550
	(0.0298)	(0.0320)	(0.0341)
Log(NumberOfHotelRooms)	-0.0105	-0.0297	-0.0384

	(0.0259)	(0.0279)	(0.0284)
Average # of Stars	0.0369	0.0304	0.0549
	(0.0516)	(0.0473)	(0.0517)
Log(HomesDensity)		-0.359	-0.300
		(0.221)	(0.195)
Log(ShopsDensity)		0.402*	0.315
		(0.213)	(0.190)
Log(OccupiedHomes)		-0.0951	0.0629
		(1.565)	(1.562)
Log(RentingFamilies)		-0.431**	-0.446***
		(0.158)	(0.142)
Log(CommercialBuildings)		-0.267	-0.283
		(0.230)	(0.226)
Constant	8.369***	8.263***	7.790***
	(0.209)	(0.357)	(0.397)
Observations	189	189	189
R-squared	0.423	0.580	0.605
Year-semester FE	YES	YES	YES
Neighbourhood Band FE			YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 17. Regression on home prices using data from OMI.

The first difference that can be noticed from Table 16 is, across the three specifications, a lower R^2, meaning that a lower share of variability is now captured by the model. Starting from the first column, Airbnb density is significant and positively correlated with home prices: a 1% increase in density leads to a 0,137% increase in prices, which is close to the coefficient found in Table 16 for the same specification.

Once neighbourhood characteristics are added (column 2), the estimate for the coefficient referring to Airbnb density is lower, but the variables describing shops density and the share of families living in a rented home are found to be significant. As in Table 16, the share of renting families and home prices are negatively correlated, albeit the coefficients are slightly different. Shops density is still positively correlated with home prices, but its significance is lower now (90% with OMI data compared to the 95% significance with Idealista). However, a 1% increase in the density of shops is estimated to inflate home prices by approximately 0,4%, which is in line with previous results.

Up to now, the results obtained with OMI values are consistent with the ones found with Idealista's; however, once neighbourhood band fixed-effects are included, all variables except for *Log(RentingFamilies)* lose their significance, even if the R-squared indicator improves from 0,58 to 0,605. This loss of significant variables is not good but it is not dramatic as well. Indeed, OMI data is available for semesters and not quarters, which means that a lower number of datapoints can be used, and the granularity and detail of price evolutions are harder to grasp. Moreover, the way the data is collected is different, and this allows for differences in results. Hence, it is possible to say that the results are coherent across the two datasets and that Airbnb has impact on home prices.

Chapter 5

Conclusions

This work investigated the potential impact of Airbnb on the real estate market in the city of Turin. The empirical work started with an analysis aimed at understanding which factors affect the profitability of a listing. To provide a solid answer, the model that has been built takes into account both the features of the property being analysed, and neighbourhood characteristics. The results show that when a listing is classified as a *commercial listing*, or when it is an *entire home*, it is able to generate significantly higher revues. Moreover, the dimensions of the listing and its rating are also indicators of higher revenues. On the other hand, variables describing neighbourhood characteristics have not been found significant, meaning that the right commitment and marketing award the best listings, while location does not necessarily lead to an advantage in terms of revenues.

Subsequently, the analysis focused on the impact on rents and home prices. The influence of Airbnb on both variables has been estimated using data from both Idealista and OMI, so that four sets of regressions have been created. Across all regressions, the variable of interest is 'Airbnb density', while other variables included in the model concern the presence of hotels, socio-economic factors, and neighbourhood characteristics. Overall, results are coherent and consistent across the specifications, and they suggest that Airbnb presence does have an impact on the real estate market, for both rents and home prices.

The findings show that a higher Airbnb density leads to higher rents and house prices, and that the effect is larger for house prices. Indeed, a 1% increase in Airbnb density is associated with a 0,0561% increase in rent prices, while sale prices increase by 0,111%. Part of this increase is due to the fact that a lower number of homes is available on the market, but the higher elasticity found for home prices leaves space for an additional interpretation. Indeed, home prices rise more than rental rates because potential home-owners are now presented with an additional income stream from their homes, which increases the valuation of the asset.

The entity of these findings is consistent with previous studies that investigated the phenomenon in other European cities but, for the city of Turin, the consequences are slightly different. Indeed, the city has not suffered from price inflation on either rents or property values, and housing affordability is not a primary problem for its residents. On the contrary, house prices have been declining for almost a decade, while rents have experienced a decline, then stagnation, and only recently they slowly started their recovery. This means that Airbnb should not be seen as a threat to the city or its residents, but rather as an opportunity from which everyone could benefit, thanks to tourist inflows for example.

Further developments of this work could investigate the opportunities brought by Airbnb and its effect on the city as a whole, for instance considering the economic activity generated by tourists. Also, it is important to note that many studies highlight how population increases are associated with increased housing costs for residents. Demographic aspects have not been included in this work since the number of residents in the city of Turin has been roughly the same across the observing period, apart from a 3% decrease that occurred between 2013 and 2019. However, further developments of this work may include demographic factors to better assess and compare the impact of Airbnb across cities with different demographics.

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Appendix

Exhibit 1. Airbnb Business Model Canvas. (From: https://bstrategyhub.com/airbnb-business-model-how-does-airbnb-make-money/).

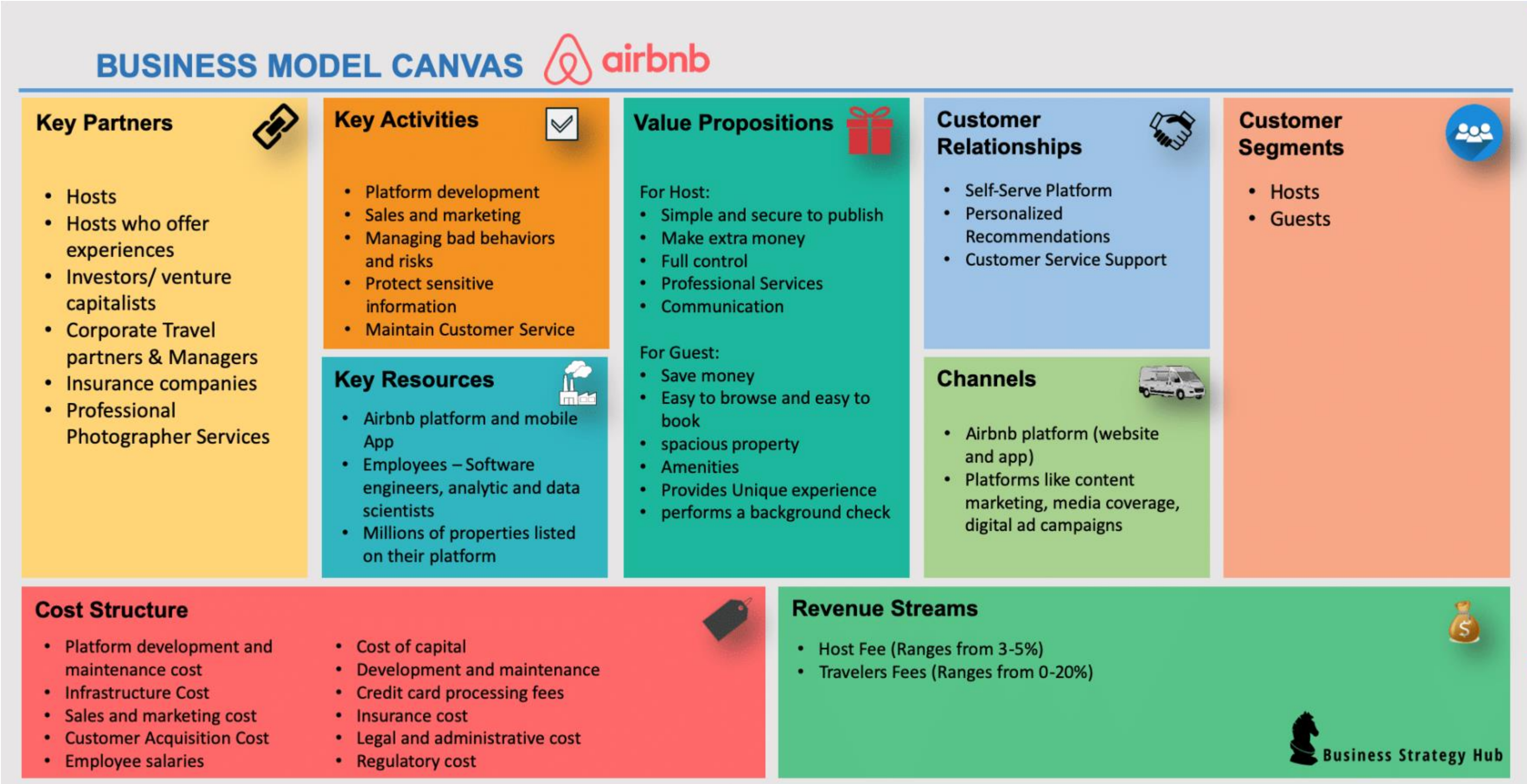

Exhibit 2. Overlap matrix created to define a match between OMI areas (on the rows, *i*) and Idealista neighbourhoods (columns, *j*). Each cell shows the percentage of *i* that is part of *j*. OMI areas E3 and E1 do not have a proper match in any of the Idealista neighbourhoods due to missing data.

	Centro Storico	San Salvario	Crocetta	Falchera-Villaretto	Barriera di Milano	Rebaudengo	Regio Parco-Barca-Bertolla	Vanchiglia	Sassi-Madonna del Pilone	Aurora	Mirafiori Nord	Santa Rita	Lingotto	Nizza-Millefonti	Mirafiori Sud	Pozzo Strada	Cenisia	San Paolo	Borgata Lesna	Cit Turin	Vallette	Madonna di Campagna	Borgo Vittoria	Lucento	Campidoglio	Parella	San Donato
B1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B4	0,77	0	0,23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B5	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B6	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B7	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B8	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B9	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C2	0	0,85	0,15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C3	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C4	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C5	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C6	0,12	0	0,18	0	0	0	0	0	0	0	0	0	0	0	0	0	0,51	0	0	0,19	0	0	0	0	0	0	0
C7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,56	0	0	0	0	0	0	0,44
C8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,15	0,85
C9	0,32	0	0	0	0	0	0	0	0	0,68	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C10	0	0	0	0	0,38	0	0	0	0	0,62	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C11	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,27	0,73	0	0	0	0	0	0	0	0	0
C15	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C16	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
D2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
D3	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
D4	0	0	0	0	0	0	0	0	0	0	0	0	0,48	0,29	0,23	0	0	0	0	0	0	0	0	0	0	0	0
D5	0	0	0,03	0	0	0	0	0	0	0	0,36	0,39	0,19	0	0,03	0	0	0	0	0	0	0	0	0	0	0	0
D6	0	0	0	0	0	0	0	0	0	0	0,05	0	0	0	0,95	0	0	0	0	0	0	0	0	0	0	0	0
D7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,61	0,10	0,04	0	0,08	0	0	0	0	0,06	0,11	0
D8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,21	0	0	0,19	0	0	0	0	0	0,12	0,48	0
D9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,18	0	0,33	0,04	0	0,45
D10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,45	0,36	0,19	0	0	0
D11	0	0	0	0	0,54	0,11	0	0	0	0,10	0	0	0	0	0	0	0	0	0	0	0	0	0,25	0	0	0	0
D12	0	0	0	0	0,38	0,42	0,21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
D13	0	0	0	0,43	0	0	0,01	0	0	0	0	0	0	0	0	0	0	0	0	0	0,17	0,14	0,08	0,05	0	0,11	0
D14	0	0	0	0	0	0	0,51	0,49	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
D15	0	0	0	0	0	0	0,69	0	0,31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
E1	0	0	0	0	0	0	0	0	0,50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
E2	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
E3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Totale	7,201	2,852	5,591	0,429	1,294	0,525	1,414	1,493	2,812	1,404	0,413	0,388	0,675	2,287	1,211	0,828	0,881	0,770	0,186	0,823	0,168	0,768	0,697	0,573	0,214	0,862	1,741

Exhibit 3. Airbnb density for each neighbourhood across the time period considered.

Neighbourhood	2014q4	2015q1	2015q2	2015q3	2015q4	2016q1	2016q2	2016q3	2016q4	2017q1	2017q2	2017q3	2017q4	2018q1	2018q2	2018q3	2018q4	2019q1	2019q2	2019q3	2019q4
Centro Storico	1,1%	1,3%	1,7%	2,1%	2,5%	2,9%	3,1%	3,3%	3,7%	4,1%	4,2%	4,3%	4,4%	4,5%	4,6%	4,8%	4,7%	4,8%	5,0%	5,2%	5,1%
Aurora	0,5%	0,6%	0,9%	1,0%	1,2%	1,4%	1,5%	1,7%	1,9%	2,1%	2,2%	2,3%	2,4%	2,5%	2,7%	2,8%	2,8%	2,8%	2,9%	3,0%	3,0%
Barriera di Milano	0,1%	0,1%	0,1%	0,2%	0,2%	0,2%	0,2%	0,3%	0,3%	0,4%	0,5%	0,5%	0,5%	0,5%	0,6%	0,6%	0,6%	0,7%	0,8%	0,8%	0,8%
Borgata Lesna	0,0%	0,0%	0,0%	0,0%	0,0%	0,1%	0,0%	0,1%	0,1%	0,1%	0,1%	0,1%	0,1%	0,1%	0,1%	0,1%	0,1%	0,1%	0,1%	0,1%	0,2%
Borgo Vittoria	0,1%	0,1%	0,1%	0,2%	0,2%	0,2%	0,2%	0,2%	0,2%	0,3%	0,3%	0,3%	0,2%	0,2%	0,3%	0,3%	0,4%	0,4%	0,5%	0,5%	0,5%
Campidoglio	0,2%	0,4%	0,5%	0,7%	0,8%	1,0%	1,0%	1,1%	1,3%	1,4%	1,6%	1,7%	1,6%	1,6%	1,7%	1,7%	1,8%	1,8%	1,8%	1,8%	1,9%
Cenisia	0,2%	0,3%	0,5%	0,6%	0,7%	0,8%	0,8%	0,9%	1,1%	1,1%	1,3%	1,4%	1,3%	1,4%	1,4%	1,5%	1,5%	1,5%	1,6%	1,6%	1,5%
Cit Turin	0,2%	0,3%	0,4%	0,5%	0,7%	0,9%	0,9%	1,0%	1,1%	1,2%	1,3%	1,4%	1,4%	1,4%	1,5%	1,7%	1,7%	1,8%	1,9%	1,9%	1,8%
Crocetta	0,2%	0,3%	0,4%	0,5%	0,7%	0,8%	0,8%	0,9%	1,1%	1,2%	1,2%	1,3%	1,3%	1,3%	1,4%	1,4%	1,4%	1,4%	1,5%	1,5%	1,5%
Falchera-Villaretto	0,0%	0,0%	0,0%	0,1%	0,1%	0,1%	0,1%	0,1%	0,1%	0,1%	0,1%	0,1%	0,1%	0,1%	0,1%	0,1%	0,1%	0,1%	0,1%	0,1%	0,1%
Lingotto	0,1%	0,1%	0,2%	0,2%	0,3%	0,3%	0,3%	0,3%	0,4%	0,5%	0,5%	0,5%	0,5%	0,6%	0,6%	0,6%	0,6%	0,6%	0,7%	0,7%	0,7%
Lucento	0,0%	0,1%	0,1%	0,1%	0,2%	0,2%	0,2%	0,2%	0,3%	0,3%	0,3%	0,4%	0,4%	0,4%	0,4%	0,5%	0,4%	0,4%	0,4%	0,5%	0,4%
Madonna di Campagna	0,0%	0,0%	0,0%	0,0%	0,1%	0,1%	0,1%	0,2%	0,2%	0,2%	0,3%	0,3%	0,3%	0,3%	0,3%	0,3%	0,3%	0,3%	0,4%	0,4%	0,4%
Mirafiori Nord	0,0%	0,0%	0,1%	0,1%	0,1%	0,1%	0,1%	0,1%	0,2%	0,2%	0,2%	0,2%	0,3%	0,3%	0,3%	0,3%	0,3%	0,3%	0,3%	0,4%	0,3%
Mirafiori Sud	0,1%	0,1%	0,1%	0,1%	0,1%	0,1%	0,2%	0,2%	0,2%	0,3%	0,3%	0,3%	0,3%	0,3%	0,4%	0,4%	0,4%	0,4%	0,5%	0,6%	0,6%
Nizza-Millefonti	0,1%	0,2%	0,2%	0,3%	0,4%	0,4%	0,5%	0,6%	0,7%	0,8%	0,8%	0,8%	0,8%	0,9%	1,0%	1,0%	1,0%	1,1%	1,1%	1,2%	1,1%
Parella	0,1%	0,1%	0,1%	0,2%	0,2%	0,3%	0,3%	0,3%	0,4%	0,5%	0,5%	0,5%	0,5%	0,5%	0,5%	0,6%	0,6%	0,6%	0,6%	0,6%	0,6%
Pozzo Strada	0,1%	0,1%	0,1%	0,1%	0,1%	0,2%	0,2%	0,2%	0,3%	0,3%	0,3%	0,4%	0,4%	0,4%	0,4%	0,5%	0,5%	0,5%	0,5%	0,5%	0,5%
Rebaudengo	0,0%	0,0%	0,0%	0,0%	0,0%	0,1%	0,1%	0,1%	0,1%	0,1%	0,1%	0,1%	0,1%	0,2%	0,2%	0,2%	0,1%	0,1%	0,1%	0,2%	0,2%
Regio Parco-Barca-Bertolla	0,0%	0,0%	0,1%	0,2%	0,2%	0,2%	0,2%	0,3%	0,3%	0,3%	0,3%	0,3%	0,3%	0,4%	0,3%	0,4%	0,4%	0,5%	0,5%	0,5%	0,5%
San Donato	0,3%	0,4%	0,5%	0,6%	0,7%	0,8%	0,9%	1,0%	1,2%	1,3%	1,4%	1,4%	1,4%	1,5%	1,6%	1,7%	1,6%	1,7%	1,8%	1,9%	1,9%
San Paolo	0,1%	0,1%	0,2%	0,3%	0,3%	0,3%	0,3%	0,4%	0,5%	0,5%	0,5%	0,6%	0,6%	0,6%	0,6%	0,6%	0,6%	0,6%	0,6%	0,6%	0,6%
San Salvario	0,7%	0,9%	1,2%	1,5%	1,8%	2,1%	2,2%	2,5%	2,8%	3,1%	3,4%	3,4%	3,4%	3,6%	3,9%	3,9%	3,9%	3,9%	3,9%	3,9%	3,8%
Santa Rita	0,1%	0,1%	0,1%	0,2%	0,3%	0,3%	0,4%	0,4%	0,5%	0,6%	0,6%	0,6%	0,6%	0,6%	0,7%	0,7%	0,7%	0,7%	0,7%	0,7%	0,7%
Sassi-Madonna del Pilone	0,2%	0,3%	0,4%	0,5%	0,6%	0,7%	0,8%	0,9%	0,9%	1,0%	1,1%	1,1%	1,2%	1,2%	1,3%	1,4%	1,4%	1,4%	1,4%	1,3%	1,3%
Vallette	0,1%	0,1%	0,1%	0,1%	0,2%	0,2%	0,2%	0,3%	0,3%	0,4%	0,4%	0,5%	0,4%	0,4%	0,4%	0,5%	0,5%	0,5%	0,5%	0,4%	0,4%
Vanchiglia	0,4%	0,5%	0,7%	0,9%	1,1%	1,3%	1,4%	1,5%	1,7%	1,9%	2,0%	2,1%	2,1%	2,1%	2,2%	2,4%	2,3%	2,3%	2,3%	2,3%	2,3%

Exhibit 4. Average home prices posted on Idealista (€/m²).

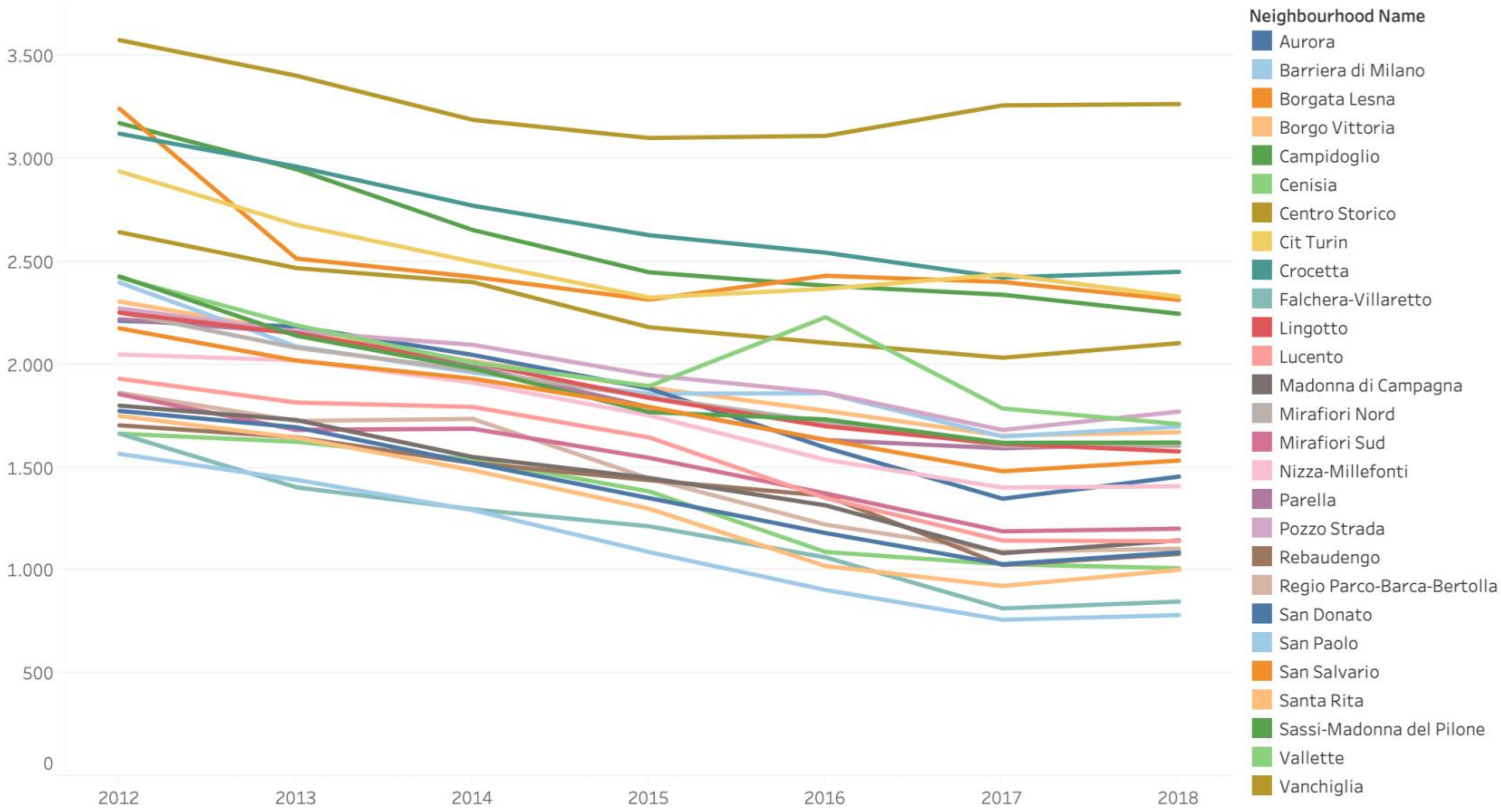

Exhibit 5. Average rent prices posted on Idealista (€/m^2 per month).