

doctoral dissertation

THE ECONOMICS OF AIRBNB

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XXXV Cycle

Acknowledgements

This dissertation is the result of work of my three years PhD at Politecnico di Torino, where I met great scientists who helped me to understand the difficult, still satisfying, art of research.

First, I am indebted to my academic supervisors, Luigi Buzzacchi and Emilio Paolucci. Throughout the entire PhD they have provided me a valuable support, helping me understanding better the theoretical argumentations of the phenomenon, as well as the main empirical issues to detect them in real world data. Furthermore, I am grateful to my supervisors for allowing me to have the opportunity to disseminate the results of the research in various academic conferences and within different academic courses at Politecnico di Torino.

Second, I am grateful to all the professors I have collaborated with during these years: Elisabetta Raguseo, Luca Grilli, Federico Caviggioli, Antonio Demarco, Francesca Governa, Chiara Iacovone and all the other professors at Politecnico di Torino. We have conducted very interesting research, although not all of them could have been included into this dissertation. I am also grateful to FULL (The Future Urban Legacy Lab) for the valuable support during these years.

Third, I am grateful to Ulrich Gunter and Bozana Zekan for hosting me in the Tourism and Service Management Department at Modul University Vienna. During my stay, I have learnt a lot on how a higher education institute can make an impact in the tourism domain.

Finally, I thank Professors Evila Piva and Antonio Messeni Petruzzelli for their valuable suggestions to improve this doctoral dissertation.

Abstract

This dissertation deals with the phenomenon of Airbnb, which, over the last years, has disrupted the hospitality industry and consequently putted itself at the forefront of the sharing economy or, in general, of the increasingly important diffusion of the digital multi-sided platforms.

To the extent that the reach of Airbnb has been global, embodying relevant implications for multiple stakeholders, this thesis provides multiple empirical analyses on Airbnb related topics, showing either intra-platform effects or platform-to-local economy ones. The analyses, as well as the common thread of the dissertation, are carried out taking a novel point of view into the digital platforms' literature. Indeed, despite treating Airbnb as a marketplace matching supply and demand in a "fictitious" delocalized market, this thesis contends that the platform offers localized services, such that the different economic concepts related to the platform are interpreted with a tight connection to local, spatially located, economic variables.

In a nutshell, the research provided by this doctoral dissertation are as follows:

a. First, dealing with the multi-sided market structure of the platform, the thesis empirically estimates cross-side externalities, providing a spatial variation of the phenomenon according to the local industry structure.
b. Second, this thesis enters into the detail of Airbnb producers' side, analyzing the entry determinants of different kind of entrepreneurs (small-scale and large-scale ones) in response to local market conditions.
c. Third, drawing on the differences highlighted in the previous chapter, the thesis discusses to what extent different kind of entrepreneurs differently act on prices, also providing a novel estimation procedure for Airbnb price equation.
d. Finally, by inverting the point of view and assessing to what extent the local diffusion of the platform can fulfill local economic conditions and local entrepreneurial activity in marginal areas, this thesis closes a notable research gap in response to the large body of literature who have notably highlighted the negative externalities generated by platforms (i.e., Airbnb) in urban contexts.

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Introduction

Over the last years, the sharing economy is dominating the scene within several industries, challenging and disrupting many traditional sectors such as hospitality and transportation (Guttentag, 2015), or creating brand-new markets thanks to the innovations embedded into the digital technologies that are facilitating the diffusion of the sharing paradigm. The emergence of the sharing economy has, in fact, paired with the growth and diffusion of global multi-sided digital platforms (or cybermediaries, according to Caillaud & Jullien, 2001), which bring together two or more distinct groups of users, typically producers and consumers of a given service/product, who need each other in some way (Evans, 2009; Hagiu, 2006). To this extent, by matching and concentrating supply and demand in a unique (digital) market, platforms create valuable interactions (which would not have occurred without the intermediation of the platform) minimizing transaction and search costs (Evans & Schmalensee, 2007) and, in the case of sharing-based markets, enabling individuals to exploit underutilized assets by allowing temporary usage to those who effectively need them (Frenken & Schor, 2017). Nowadays the importance reached by digital platforms is clear, either looking at the main incumbents active in the market or looking at innovation processes. Indeed, if on the one side the most valuable companies in the world are based on the multi-sided digital platform business models (e.g., Apple, Amazon, Google, Microsoft), on the other side the majority of the novel successful new ventures (i.e., startups) is actually proposing a *cybermediary* value proposition (Cusumano et al., 2020). However, if it is true the digital platforms are providing extremely valuable services to both producers and consumers (clearly recognized by the market), on the other hand it is also true that the diffusion of these firms is generating externalities on society (Barron et al., 2021; Burtch et al., 2018; Farronato & Fradkin, 2022; Garcia-Lopez et al., 2020), whose effects are still discussed by researchers (Zervas et al., 2017; Farronato & Fradkin, 2022). To this end, given the notable contributions to the economy, and the relevant implications that may derive (for both managers practitioners and policy makers), the literature on digital platforms has rapidly grown, providing multiple contributions, either theoretical or empirical (see De Reuver et al., 2018, for a complete survey of literature and a future research agenda on digital platforms).

In line with the flourishing research streams around digital platforms, this thesis enters the current academic debate assessing multiple research questions and providing significant contributions to the academic knowledge on platform-based markets with relevant implications for different stakeholders such as managers, entrepreneurs, and policy makers. The testbed, as well as the first common thread, of the following doctoral dissertation is Airbnb (https://www.airbnb.com), one of the leading examples of digital sharing-based platforms (Guttentag et al., 2015), able to disrupt the traditional hospitality industry (Zervas et al., 2017; Farronato & Fradkin, 2022) with effects spanning well beyond the respective industrial sector as it is becoming also relevant in determining local social welfare (Barron et al., 2021; Chen et al., 2022). At a glance, in order to quantify the disruptive potential of Airbnb, in few years of operations only (i.e., from 2008 up to 2022), the platform has been able to achieve a global reach, counting over four million hosts active in 220 different

countries, more than one billion guests hosted[1] and overcoming the quantities offered by traditional service providers (i.e., hotels)[2]. To this end, as confirmed by the growing literature upon this topic (Zervas et al., 2017; Farronato & Fradkin, 2022; Chen et al., 2022; Barron et al., 2021; Gerwe et al., 2020), Airbnb can be considered as a relevant example to study digital-based markets and the corresponding implications, also considering the peculiarities of this platform (as compared to other existing ones), which pave the way for further research questions that still have to be answered. Indeed, at a higher level, Airbnb can be considered as a particular kind of platform, as long as it is possible to mark a clear distinction among platforms.

On the one hand, digital platforms such as C2C e-commerce (Chu & Manchanda, 2016) or crowdsourcing websites (Dushnitsky et al., 2022) are typically thought as services that match supply (i.e., producers) and demand (i.e., consumers) on a single de-localized "fictitious" market without geographical borders (Kim et al., 2022), which in absence of the platform would have been resulted in smaller localized segmented markets (i.e., referring to the case of Amazon, without the digital de-localized market provided by Amazon e-commerce, the consumption of matches would occur in traditional, localized, retailing markets). On the other hand, platforms such as Airbnb, or Uber (Burtch et al., 2018), even if are still based on a digital multi-sided market organization, matching supply and demand in efficient ways, offer localized services (i.e., services that are directly linked to a physical, geographically segmented, market), generating effects that are peculiar to this platform structure. This special characteristic of Airbnb, which represents the second common thread of this doctoral dissertation, makes the hospitality platform an interesting case study, since multiple aspects of the traditional economic processes studied in the platform literature are profoundly linked to its physical nature, still they have not yet been carefully studied by the extant research. To this extent, this thesis, addresses four concepts related to the platform-based markets, including in the theoretical formulation of the arguments the novel point of view of the spatially segmented platform. First, as long as platform-based markets are strongly characterized by cross-side network externalities (CNE) (Katz & Shapiro, 1985; Parker & Van Alstyne, 2005), this thesis offers a spatial characterization of the economic phenomenon, providing an empirical estimate on the Airbnb platform, as well as showing how the intensity of CNE varies across geographically segmented sub-markets. Second, to the extent that Airbnb offers different entrepreneurial opportunities to different kind of entrepreneurs (Dogru et al., 2020), this thesis offers a study on the entry determinants of small-scale and large-scale entrepreneurs into the platform, focusing on the competition mechanisms as long as oversupply (proxied by the carrying capacity concept of Hannan & Freeman, 1977, or Carree & Thurik, 1999) has a relevant aspect to the extent that the services offered by Airbnb are purely localized in space. Third, proceeding with the distinction between different kinds of entrepreneurs, this dissertation makes a further step in the

[1] Further information about the global diffusion of Airbnb is available at the following source. Airbnb (2022). About us. Link: https://news.airbnb.com/about-us/.

[2] Further information is available at the following source. Dina Gerdeman (2018), The Airbnb Effect: Cheaper Rooms for Travelers, Less Revenues for Hotels. Harvard Business School, Working Knowledge. Link: https://hbswk.hbs.edu/item/the-airbnb-effect-cheaper-rooms-for-travelers-less-revenue-for-hotels

determinants of one of the main strategic decisions taken by Airbnb service providers, i.e., pricing (Sainaghi et al., 2021), linking the posted price-per-night with local demand shocks faced by each Airbnb host, and also providing a novel empirical/methodological contribution. Finally, by reversing the point of view, this thesis studies the effects of the local diffusion of Airbnb on local entrepreneurial activity, contributing to the literature on the effects of platforms' diffusion on local economic welfare (Farronato & Fradkin, 2022; Chen et al., 2022) assessing a peculiar geographical segment. Figure I.1. synthetizes the research framework conceptualized by the thesis, providing a glimpse on the main relationships analyzed throughout the entire dissertation.

[Insert Figure I.1. here.]

The present dissertation provides answers to these topics employing quantitative methods (namely, econometric analyses) relying on a wide and comprehensive database on Airbnb, spanning throughout Europe, and furnished by the world-leading provider AirDNA (https://www.airdna.co). The raw data used for the purposes of these analyses, contains granular panel listing-level information, including meta-data on entry and exit date, as well as performances and geographical location of the Airbnb properties, such as various aggregations of different economic metrics (i.e., entries, demand, beginning of diffusion, local penetration; depending on the nature of the research questions) have been computed. Consistently, in line with the research topics, data on Airbnb activity have been merged with different data sources, including information coming from either public databases (i.e., ISTAT, https://www.istat.it, for Italian scale analyses, or Eurostat, https://ec.europa.eu/eurostat/de/data/database, for European scale ones) or private ones (e.g., data from the register of companies owned by Italian Chamber of Commerce, https://www.registroimprese.it, which have been used in the last chapter). Furthermore, to the extent of providing consistent estimates of the effects investigated in this thesis, state of art econometric methodologies have been employed, spanning from traditional Two-Stage-Least-Squares and GMM-SYS methods (Blundell & Bond, 1998) to novel causal inference methods such as continuous treatment difference-in-difference (Callaway et al., 2021) or panel event study approach (Clarke & Tapia-Schynte, 2022; Angrist & Pischke, 2008). In this sense, this dissertation, along with contributing to the current academic literature with both theoretical and practical/managerial findings, provides further contributions to researchers by testing and proposing novel econometric frameworks to Airbnb empirical applications.

The rest of this dissertation is structured in four main chapters, each proposing a separate analysis on a specific topic/research question.

The first chapter addresses the concept of Cross-Side Network Externalities (CNE) within a spatially segmented platform, investigating magnitude and spatial heterogeneity of the economic phenomenon. As digital platform based on a multi-sided market structure, Airbnb is indeed characterized by the presence of CNE (early defined by Katz & Shapiro, 1985, or Evans, 2003) as long as the users' utility of participating to the platform market (on every side) depends on the joint decision of participants on the other/same side of the platform in several opposing ways, positive or negative (Filistrucchi

et al., 2012; Weyl, 2010). According to Parker and Van Alstyne (2005), network externalities are either the main source of value creation (i.e., they can lead to the impressive growth rate of platforms user-base), or, at once, one of the main sources of failures in multi-sided markets businesses (see for instance the literature on platform launching strategies, often referring to the concept of chicken-egg problem, Caillaud & Jullien, 2003). In response to the significant role of CNE within a platform-based business, the empirical literature has provided a conspicuous body of research, starting from Rysman (2004) up to the most recent works of Chu & Manchanda (2016), Hinz et al. (2020) and Kim et al. (2022). In line with the scope of the thesis, and with the recent intuition of Kim et al. (2022), this thesis investigates CNE in a novel spatial point of view, complementing the former literature which has provided only a time-characterization (Chu & Manchanda, 2016), as long as the magnitude of producers to consumers (and vice-versa) elasticities will be allowed to vary across different local markets according to the local industry structure of the reference industry (in this case, the hospitality one). At a glance, the empirical analysis, based on a utility-based theoretical model, and employing a 2SLS panel estimation with BLP-like instrument, beyond quantifying the cross-side externalities into the Airbnb platform, shows multiple results: i) producer to consumer (i.e., hosts to visitors) externalities are significantly stronger compared to consumer to demand (i.e., visitors to hosts) ones, meaning that Airbnb is primarily supply driven; ii) in sub-markets where the intensity of the whole touristic supply competition is thicker (lower) producer to consumer externalities are stronger (weaker); iii) in sub-markets with higher (lower) touristic appeal producer to consumer externalities are weaker (stronger); and iv) consumer to producer externalities do not significantly vary over local sub-markets. These results provide significant theoretical and practical implications. For instance, to test the outcome of the analysis, the chapter proposes a simulation analysis, where the marginal cost of producers is artificially increased, showing to practitioners how network externalities effectively work in reality, in this case amplifying shocks. Furthermore, in line with the idea of the localized platform and consistently with the spatial asymmetry of CNE, the simulation shows that indirect negative effects on demand are larger in sub-markets where touristic supply intensity is higher.

Starting from the limitations of the first chapter, which largely focuses on the CNE rather than on same side effects, and treats all producers as a unique undifferentiated class, the second chapter provides an in-depth study on Airbnb producer side, investigating the different entry determinants of small-scale entrepreneurs compared to large-scale ones (Dogru et al., 2020). In line with Davidsson et al. (2020), which has recently introduced the concept of external enabler in the entrepreneurship literature, stating that the entrepreneurial action can be "exerted by external conditions like new technologies, regulatory or demographic shifts, and changes to the socio-cultural, economic, political, or natural environments." (Davidsson et al., 2020; p. 311), the thesis argues that Airbnb can as external enabler for potential entrepreneurs (as similarly done by other examples in literature, like Nambisan et al., 2018), by stimulating entrepreneurial opportunities (Shane & Venkataraman, 2000; Kirzner, 1973; Schumpeter, 1912/34). In doing this, and leveraging on the spatial segmentation of Airbnb, the second chapter questions how individual decisions to pursue entrepreneurial opportunities, and the ways they eventually do it, are shaped by the specific local industry conditions of

the markets in which the global platform operates. In other terms, how does the digital enabler interact with a local market context in shaping entrepreneurial action. On the basis of these considerations, the second chapter deals with three following interrelated issues. First, it explores the extent to which the seizing of entrepreneurial opportunities potentially available because of a digital external enabler is driven by locally bounded market conditions, focusing on the role of entry costs and same side externalities. Secondly, it investigates whether there are significant differences in these local market drivers between small-scale entrepreneurs, i.e., individuals who use the platform to sell their services only occasionally, and large-scale ones, i.e., professional entrepreneurs who have created their own new business through the platform. Finally, it examines if, at local level, small scale entrepreneurship is a steppingstone towards more professional forms of entrepreneurship (i.e., large scale ones) as the view on hybrid entrepreneurship (i.e., individuals transitioning gradually from traditional employment, retaining their wage, while simultaneously entering the self-employment, Folta et al., 2010) would suggest, but at the same time, it explores if drivers of transition always respond to a sound economic logic. In a nutshell, the dynamic panel approach adopted in the analyses, estimated through a GMM-SYS approach (Blundell & Bond, 1999), shows multiple results. In particular, the chapter shows that the entry of small-scale entrepreneurs is particularly sensitive to demand dynamics and to the opportunity costs implied by the entry, but rather insensitive to supply-side factors. While equally stimulated by the size of demand, large-scale entrepreneurs are found to be much more responsive than small-scale entrepreneurs to the actual structure of the supply curve at local level and, in particular, large-scale entries are found to consist of an inverted-U-shaped in relationship to the local supply concentration. While for small-scale entrepreneurs the sunk costs of entry are admittedly low, large-scale ones have to necessarily incur some non-fully redeployable investments to carry the host activity in a professional manner. In other words, their entry appears more "reasoned" than that of a non-professional entrepreneurs. The results are interpreted based on agglomeration and (locally-bounded) information mechanisms prevailing first over a competition effect that, conversely, dominates after. Interestingly, the chapter also document a relevant probability of observing transitions from small-scale status to the large-scale one, suggesting how the two typologies of entrepreneurship do have different drivers but are not necessarily characterized by different innate attributes. Indeed, a conclusive analysis, effectively shows how status transitions from scall-scale to large scale entrepreneurship are driven by the same forces shaping large-scale entrepreneurs' entries.

In the vein of the distinction between small-scale and large-scale entrepreneurs formulated in the second chapter, the third chapter analyzes one of the most debated questions within the Airbnb literature, studying how service providers set their posted prices assessing whether differences exist between professional and non-professional service providers. In order to do so, this chapter takes advantage of the shock caused by the pandemic which, starting from March 2020, strongly affected the touristic industry causing a significant decline in the global demand and remarkably impacting the operations of Airbnb (Dolnicar & Zare, 2020), thus allowing for a quasi-experimental study. Indeed, under the evidence that the COVID-19 pandemic has shown differences in terms of timing and intensity of the various pandemic waves and

also in terms of timing and intensity of local (national, regional, …) governmental countermeasures (such as travel restrictions, lockdowns, or other precautionary actions), different Airbnb hosts, located in different European countries, have been affected quite differently by the demand variations caused by the pandemic, certainly depending on the strategies adopted at the country level to face the diffusion of COVID-19.

Grounding on these aspects (namely the discontinuity caused by Covid-19 Pandemic and the differential exposure of Airbnb listings to different pandemic-related containment strategies), and on a wide dataset of 130,999 continuously active Airbnbs throughout Europe, the third chapter studies the relationship between prices and local demand providing a novel instrumental variable, which relies on a continuous treatment approach (Callaway et al., 2021), such that the endogeneity of demand in price equation has been solved by the means of the differential exposure of local markets to the respective governmental strategies (efficiently proxied by the COVID-19 Stringency Index, published by Hale et al., 2021). Briefly, other than quantifying the effect of governments' strategies on local short-term rentals' demand, the analyses show that, coeteris paribus individual and time-varying factors, and accounting for endogeneity of demand, hosts facing rising demand are on average prune to set prices upwards. However, further refinements show that this difference is heterogeneous across host types, being prices of professional (i.e., large-scale) hosts significantly varying upwards as of demand increases, while prices posted by non-professional (i.e., small-scale) service providers are typically driven by hedonic-style variables (e.g., listing typology, dimension, distance to city center, amenities offered, …), effectively captured by listing-level fixed effects, thus confirming the findings on the differential behavior and skill-set of small-scale and large-scale entrepreneurs shown in the second chapter.

Finally, consistently with the idea of spatially localized platform, the fourth chapter reverses the point of view. Indeed, if the first three contributions have focused on how local market conditions can shape the decisions and the growth of the platform market Airbnb, this last section assesses whether and how the platform can shape and have impact on contextual local market conditions, and more generally, local economic welfare. In doing so, the fourth chapter enters the growing debate about the side effects of digital platforms, which is rather flourishing over the last years, with a (new) layer which has been rather neglected by previous research. Indeed, while the topics covered are various, ranging from regulation of peer-supply (Chen et al., 2022) to the estimation of platform diffusion on consumer welfare (Farronato & Fradkin, 2022), scholars have often concentrated on the impact of online platforms in a specific market context, the urban one (Carrasco-Farré et al., 2022). This chapter contends that, given the different market conditions, the effects in marginal economic contexts, that are typically characterized by an economy which struggles to grow, can be different. Indeed, if on the one side, when entering urban markets platform typically compete with the corresponding traditional services by substituting or displacing them (Zervas et al., 2017; Chen et al., 2022; Burtch et al., 2018), it is likely that in marginal areas the effects can be opposite. In particular, rather than being competitors or substitutes, when entering marginal areas, the chapter argues that platforms can act as developer of new economic processes, creating an offer which can be

complemented by new services. In other words, in such cases platform create novel entrepreneurial opportunities (Shane & Venkataraman, 2000), acting as external enabler (Davidsson, 2015; Davidsson et al., 2020) for entrepreneurs, in this case external to the platform market (as opposed to the second chapter, where entrepreneurs working *into* the platform are analyzed). Ultimately, to the extent that this process of value creation involves entrepreneurs willing to pursue their newly created opportunities within the local market, this chapter argues that these externalities can be internalized by the local area, thus fulfilling an endogenous growth mechanism, deriving important implications for local policy makers. In order to add evidence to the debate, this chapter answers the question of whether the entry of Airbnb in rural/marginal areas is able to create novel entrepreneurial opportunities, which in turn can stimulate the entry of entrepreneurs (proxied by the income from declared entrepreneurial activity, as done in literature by Burtch et al., 2018). These arguments are tested on a specific empirical setting, the Italian Borghi (namely "*small town, or an aggregation of small municipalities, with a small living population in which an historical borgo has to be clearly identifiable and visible. In case of very small Borghi, the historical part can constitute the whole municipality*" according to the Italian Ministry for Culture), which offer a unique opportunity to examine the impact of an home-sharing digital platform entering into a local rural market since a) they represent markets in marginal economic conditions being characterized by declining economic metrics, b) they are characterized by the presence of relevant assets for touristic purposes (e.g., typically in line with the definition of the Italian Ministry for Culture they are characterized by the presence of an historical center) which combines with the potential effects that a platform like Airbnb can provide, and c) they provide an experimental situation to the extent that among the 270 officially recognized Borghi, only a subset of them has been affected by the entry of Airbnb, thus suggesting an experimental approach as an appropriate control group is clearly recognizable (i.e., Borghi not affected by the entry of Airbnb) (Burtch et al., 2018). At a glance, the fourth chapter shows that following the entry of Airbnb in a Borgo, differential effects in the short and long run exist. In particular, while immediately after the first Airbnb opening no significant effects on entrepreneurial metrics are found, in the long run a significant effect is likely to hold. In particular, from four years onwards since Airbnb exposure, entrepreneurial-income declarations are willing to be 23.6% higher. For a median Borgo, this translates into 361 k€ more declared by entrepreneurs per year starting from four years after the entry of Airbnb. Second, to the extent of showing the mechanisms behind the creation of these opportunities, the analyses distinguished these effects by market sectors showing that service sectors (e.g., transportation, restoration) closer to the hospitality industry are quasi-immediately impacted by Airbnb. Furthermore, plausibly towed by the local economic growth, in the long run, also upstream sectors (i.e., primary and manufacturing) benefit from the entry of Airbnb, showing that these value creation mechanisms are willing to hold through all the local value chain. Finally, the results further show that within the Italian Borghi case study the positive effects on entrepreneurial income are not paired by processes of increasing income inequality and residential displacements.

Although tackling multiple topics, this doctoral dissertation offers a precise understanding of the economic mechanisms driving the growth and the diffusion of Airbnb, one of the leading examples of digital platforms and sharing economy. In

general, this thesis provides a novel framework under which understanding and assessing platforms, embracing the recent intuition of Kim et al., (2022), who have been, at the best of author's knowledge, the first to introduce the concept of space into the definition of global multi-sided platforms. Following this contribution, several takeaways are likely to be derived, spanning from implications to academic researchers and industry practitioners or policy makers (that will be separately discussed in each chapter). In this sense, to the extent that this dissertation largely contributes to the literature on entrepreneurship connected to digital platforms, relevant instruments for policy makers, especially those planning for economic growth in marginal areas, are provided.

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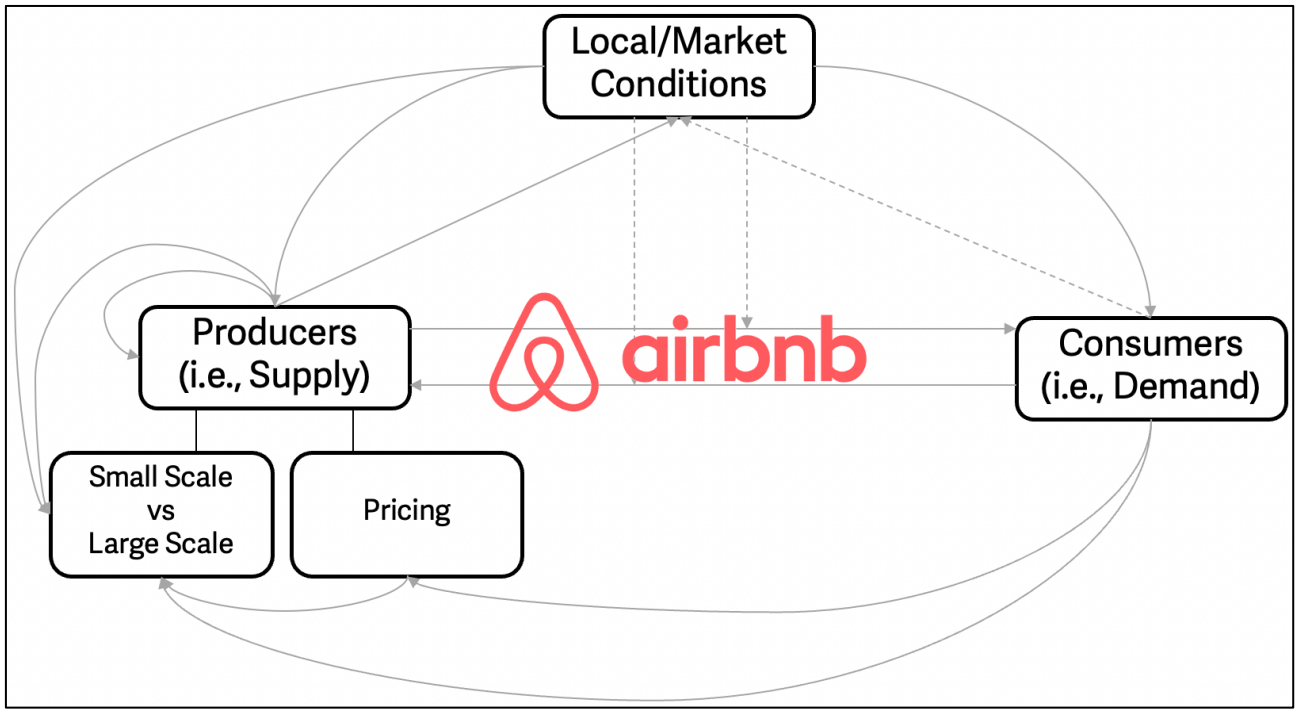
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Figures - Introduction

Figure I.1. Research Framework of the doctoral dissertation.



CHAPTER 1

Cross Side Network Externalities in geographically separated multi-sided platforms: evidence from Airbnb

Abstract

In recent years many traditional industrial sectors faced the entry of digital-based multi-sided platform that are rapidly raising significant importance within the global economy. To this extent, researchers have focused on the economic study of multi-sided market structures, with a specific focus on the network structure and the cross-side externalities (CNE) between the multiple sides of the market. Given the important theoretical and practical implications, the literature on the empirical estimate of CNE has flourished. In this vein, this chapter quantitatively estimates the magnitude of CNE into the Airbnb platform pointing out a novel spatial characterization of the economic phenomenon. Indeed, as long as Airbnb platform offers localized services and is thus composed by multiple geographically separated sub-markets, this research shows that CNE vary according to the local industry structure, as well as showing that Airbnb is primarily supply driven. With the aim of providing practical implication, the findings are than analyzed in a simulation setting, showing relevant insights for practitioners.

Keywords

Digital Platforms; Multi Sided Markets; Network Externalities; Airbnb

Credits & Acknowledgments

The author thanks the PhD supervisor, Prof. Luigi Buzzacchi, and the participants to the XXXVI Jornadas de Economia Industrial (JEI 2022; taken in Las Palmas de Gran Canaria, 1-2 September 2022) for insights and comments on earlier drafts of the research.

1.1. Introduction

This chapter tackles one of the most relevant phenomena within multi-sided market structures, estimating and contributing to the empirical literature on cross-side network externalities (Rysman, 2004; Clements & Ohashi, 2005; Ackerberg & Gowrisankaran, 2006; Chu & Manchanda, 2016; Hinz et al., 2020; Kim et al., 2022), which are at the basis of the economic micro-foundation of multi-sided platforms (Evans, 2003; Rochet & Tirole, 2003) and the corresponding strategic management actions (Parker et al., 2016). Grounding on the extant literature and with the aim of providing relevant practical contributions (see, again, the strategic management literature on platforms' strategy and network externalities, Parker et al., 2016), this analysis addresses the concept of CNE in a novel way (Kim et al., 2022), testing whether a global multi-sided platform, offering localized services, faces different intensity of CNE across the different sub-markets it is active. Indeed, as reported in the Introduction of this doctoral dissertation, literature has often focused on de-localized multi-sided platforms (e.g., C2C e-commerce, Chu & Manchanda, 2016; or personal assistant market, Ackerberg & Gowrisankaran, 2006), which match supply and demand in a "fictitious" market structure, neglecting the peculiar spatial component of platforms such as Airbnb or Uber which offer *spatially* localized services.

In this vein, this chapter, starting from the theoretical model of Chu & Manchanda (2016), extends the literature on CNE in several ways. Firstly, assuming that each geographic sub-market is separated, this paper exploits Chu & Manchanda (2016) utility based model over a panel dataset structure, rather than a time-series one, where each panel is represented by a single sub-market; secondly, according to the panel structure of the data and the corresponding distinction of multiple sub-markets, this paper analyzes whether cross-side externalities (both producer to consumer and consumer to producers) vary according to the local characteristics of the reference industry (in this case, the hospitality sector), thus highlighting a novel characterization within the micro-foundation of multi-sided platforms (Kim et al., 2022); and finally, the results of the former analyses are applied and interpreted into a simulation context to spot the differential impact of common and equal shocks over different submarkets. In particular, this latest analysis offers a tangible explanation of CNE and the corresponding spatial characterization. Grounding on these analyses, this study offers multiple contributions relevant for both industry practitioners and the economic literature on the micro-foundation of multi-sided platforms. First, in line with Kim et al. (2022), this study confirms that, although, generally, platform-based services are *digital*, the spatial component in some platforms matters and significantly shapes the corresponding growth trajectories, thus offering a new viewpoint upon which studying the strategic management of such market structures in presence of positive (e.g., marketing efforts) or negative (e.g., exogenous occurrences) shocks on supply or demand side.

The rest of the chapter is organized as follows. Section 1.2. briefly revises the major contributions to the literature of MSM and digital platforms, Section 1.3. introduces the theoretical model, Section 1.4. presents the data and the empirical methodologies, Section 1.5. illustrates the results while Section 1.6. provides a discussion of the results and a sub-section on the directions for future improvements of the research.

1.2. Related Literature

1.2.1. A general overview on Multi-Sided Platforms Economics and Cross-Side Network Externalities (CNE)

Thanks to the increasing availability of less-aggregated data, the literature on multi-sided markets (MSM) and digital platforms has flourished over the last years. Despite it is not the objective of this thesis to draw an extensive review of the studies conducted on the topic of digital platforms (to this extent Sriram et al., 2015 provide a broad and recent review on the economics research about digital platforms), a distinction of the main research streams, as well as an in-depth focus on the empirical research on cross-side externalities is important to unveil novel aspects of this work.

Although the first contributions on network economies are old dated (see Katz & Shapiro, 1985, 1986 and 1994; or Farrell & Saloner, 1986), the first researchers (simultaneously) defining digital platforms are Evans (2003) and Rochet & Tirole (2003). On the one side, Evans (2003) defines a digital platform a market based on the presence of cross-side dependency between two or more groups, while on the other side Rochet & Tirole (2003) proposed a definition of platforms based on the correlation between asymmetric pricing structure (i.e., the different prices charged to each side for the "participation" to the platform) and the transactions' volume. Despite the two definitions appear to be distant, they are closely tied (see for a similar point of view Hagiu & Wright, 2015, or Parker & Van Alstyne, 2005, who rely the differences in the pricing schemes on the magnitude of the cross-side externalities generated by each side) and well summarize the main topics investigated under the theoretical and empirical point of view by research in digital platforms. Indeed, if on the one side the literature has produced a conspicuous body of research on theoretical predictions about the market outcomes according to the pricing structures of monopoly or competing platforms (Rochet & Tirole, 2003; Armstrong, 2006; Caillaud & Jullien, 2003), on the other side an increasingly stream of research is studying cross-side network externalities (some examples are Rysman, 2004; Ohashi, 2003, up to the more recent Chu & Manchanda, 2016; Hinz et al., 2020) under the theoretical or empirical point of view, which is the focus of this dissertation's chapter[3].

One of the first contributions in the empirical literature on cross-side externalities dates back to Rysman (2004) who has estimated the cross-side externalities into the yellow-page MSM pointing out that there are positive effects on increase in advertisers installed base on users base and vice-versa. In the same fashion, the contributions of Nair et al. (2004) and Ackerberg & Gowrisankaran (2006) show the presence of positive externalities respectively occurring between the hardware installed base and software availability in the personal digital assistant markets, and between banks and customers in the ACH market. Following Rysman (2004), the empirical contribution of Wilbur (2008) points out the cross-side effects trigger not only positive feedback loops but also negative ones (i.e., negative cross-side effects). Indeed, according to the author, in the television industry, while on the one side there is a positive externality of audience on advertiser demand, on the other side increase in advertising generates a negative effect on audience. The most recent

[3] At the intersection of the two main streams of literature, often grounding on the presence of cross-side externalities and asymmetries in the pricing structure researchers have answered multiple questions, not directly connected to the main topic of this research, such as platforms startup (i.e., chicken-egg problem, Caillaud & Jullien, 2003) or the set of strategic decision taken by the platform service provider (Parker & Van Alstyne, 2005; Parker et al., 2016).

contributions, backing to Chu & Manchanda (2016), Hinz et al. (2020) and Kim et al. (2022), embody novelties into the research stream of quantification and definition of cross side externalities. The first one, also thanks the availability of individual producers and consumer data, introduces a variation over time of cross network effects in an empirical analysis of the C2C platform Taobao showing that the demand to supply externalities are stable over time, while the supply to demand ones first increase and then decrease up to a stable value. Furthermore, the authors find that a significant asymmetry in the externalities is present, with supply to demand externalities on average about four times larger than the opposite ones, confirming the theoretical predictions about the presence of a *subsidy* side within this market structure (Parker et al., 2016). Hinz et al. (2020) provide a further methodological distinction of network externalities into effects on new potential participants on the one hand and existing participants on the other (for a total of eight network effects, considering both cross-side and same side ones) by the means of an influx-outflow model. Finally, Kim et al. (2022), provide the first, pioneering, contribution on the spatial identification of CNE, estimating that the adoption in a fantasy sport market platform is significantly asymmetric across income levels of different countries.

1.2.2. The contribution of this study: Spatially Localized Multi-Sided Platforms

Although the extant literature has estimated cross-side externalities within a wide set of platform-based markets (i.e., yellow-pages, personal digital assistance, or ACH market, etc.), the previous studies converged and studied de-localized multi-sided platforms only, neglecting the spatial components that platforms like Airbnb or Uber unveil. Indeed, what is special about a platform like Airbnb is the fact that although the matching between supply (i.e., hosts) and demand (i.e., visitors) happens on a digital marketplace, the services offered by the platform are supplied on a clearly (geographically) segmented market which is subject to market saturation, competition forces (see Zervas et al., 2017 for Airbnb case) and whose consumption is affected by locally segmented economic variables (Dogru et al., 2020). On the other hand, this is not true, for instance, for B2C or C2C e-commerce platforms, where products are supplied in a geographically un-defined marketplace, such that the role of local competition forces is negligible.

According to this assumption, this study pursues the intuition of Kim et al. (2022), who have been, among the others, the first to assume that in presence of spatially localized platforms, the magnitude of CNE can significantly vary according to the geographic segment in which the services supplied by the platform are offered. In the same spirit of Kim et al. (2022), who have shown that country income level determines the asymmetric magnitude of CNE in the same multi-sided platform across the different countries in which it is active, this dissertation envisages that the local market structure in which the service offered by the platform is supplied shapes, in the same manner of Kim et al. (2022), the intensity of CNE. In other words, this study argues that where local supply competition is thicker or exogenous local demand appeal is stronger, the supply-to-demand or demand-to-supply elasticities are, coeteris paribus, significantly different compared to those markets where competition is mild, or demand appeal is lower. With specific reference to Airbnb case study, this assumption can be interpreted as follows. In geographical markets where the presence of hotels is stronger, it is plausible to expect that supply-to-demand elasticity is different compared to markets where traditional hospitality is not well

diffused. In other words, this assumption expects the hosts, when deciding to list or not his apartment on Airbnb, to weight differently demand variations if he will face stronger or lower supply competition.

Grounding on these considerations, this study answers this explicit research question:

RQ: How does the magnitude of CNE on the same digital platforms varies according to the local industry structure in which the services offered by the platform are supplied?

In order to test these arguments, under the empirical and methodological point of view, this study builds upon the Chu & Manchanda (2016) exploiting a utility-based model to empirically estimate the cross-side network externalities into the Airbnb platform. However, specific differences, aimed at complementing their contribution, with the idea of spatially localized platforms, are likely to exists between this analysis and Chu & Manchanda (2016) one, such that a submarket-based approach can be adopted. First, while Chu & Manchanda (2016) analyze two time-series equations (i.e., the supply side model and the demand side model), this paper relies on a panel dataset of multiple sub-markets (i.e., an Italian province), each one characterized by its own supply and demand, as well as other local factors which can influence the local platform growth. Secondly, while Chu & Manchanda (2016) provides a time-varying point of view on network externalities, this paper changes the focus by postulating a market (space) variation of cross side externalities according to the local features of the industry in which the platform is competing (i.e., in this case the paper postulates that cross side externalities may vary according to the hospitality market structure, proxied by either supply or demand intensity, at the local level). In this sense, this analysis also differs and complement Kim et al. (2022), since, while the authors estimate heterogenous network externalities across income variables, this study argues that CNE can vary because of traditional industrial organization forces (supply competition and demand intensity).

1.3. Theoretical Model

This study exploits a utility-based function of producers (i.e., hosts/listings, called, for simplicity *supply*) and consumers (i.e., visitors, called for simplicity *demand*) to estimate cross side network effects on Airbnb, drawing on the methodology proposed by Chu & Manchanda (2016). Two equations are estimated, one for supply and one for demand, considering in both cases the utility of joining/using Airbnb at a specific time (month of year) t in a specific sub-market (province) p. In this empirical setting, to the extent of deriving the main equations to be estimated, Airbnb is considered as a monopolistic platform in the market and, with respect to supply, multihoming is not allowed. Thus, if one listing is available on Airbnb it cannot be available neither on any other short-term rental platform, such HomeAway (today called VRBO), or on the long-term rental market, or occupied by people. Even if this assumption could be arguable, it is reasonable to assume that within the considered Italian market Airbnb is by far recognized as the state-of-art for short-term rentals,

thus people tend to sell their properties on Airbnb primarily[4]. On the other hand, according to the literature that has recently studied the relationship between Airbnb and the long-term rental market, the assumption of exclusivity between Airbnb and long-term rents holds true as they are typically considered substitutes (Garcia-Lopez et al., 2020; Barron et at., 2021; or, particularly, Chen et al., 2022).

The rest of the section will now explore both theoretical utility models.

1.3.1. Producers' Side (Supply, i.e., Hosts/Listings) Utility Model

The net indirect utility of a listing *i* to join Airbnb at a specific time *t* in a given sub-market *p* can be synthetized by Equation 1.1:

$$U_{ipt}^{S} = f(b^{S})\, f\left(D_{tpk}, C_{pt}, I_{pt}, A_{pt}, X_{p}^{S}, X_{t}^{S}, \xi_{ipt}^{S}, \varepsilon_{pt}^{S}\right) - P_{ipt}^{S}$$

(Eq. 1.1)

This utility is dependent on an intrinsic preference for the platform b^S, the expectations on consumer demand generated on the platform D_{ptk} in sub-market *p* that the hosts owning the listing *i* has from *t* over the next *k* months (according to Cabral, 2011, this term approximates cross side network externalities) and generally on the platform, the entry/opportunity costs conditions C_{pt} that a listing *i* faces in order to entry and be active on the platform, the general income level I_{pt} in sub-market *p* at time *t*, information and agglomeration effects A_{pt} working in sub-market *p* at time *t*, sub-market specific effects which do not vary over time X^S_p such as the presence of major touristic hotspots (i.e., monuments or natural attractions) which could affect also the level of demand in the respective sub-market *p*, seasonal factors X^S_t, other unobserved characteristics to the researcher ξ^S_{itp} and the fee applied by Airbnb per each listing P^S_{ipt}. Specific considerations, referring the entry/opportunity costs, the income level and the agglomeration effects deserve to be further discussed. First, despite there is not a common definition of the opportunity/entry costs that hosts face when joining the Airbnb platform (i.e., in the standard situation, according to the classical definition of sharing economy, see Frenken & Schor, 2017, an average host already own an extra idle space and rent out it on Airbnb), two main variables varying over time and space can be considered as approximation of opportunity costs of being on Airbnb. On the one side, given the substitutability between short-term and long-term rentals (Garcia-Lopez et al., 2020; Barron et at., 2021) and the main assumption of not allowed multihoming in this empirical setting, the average rent $AvgRent_{pt}$ of Airbnb-style accommodations in sub-market *p* at time *t* can be considered as one the main opportunity cost items faced by an entering Airbnb host given that it is foregoing the returns of long-term rentals to obtain the short-term ones (Chen et al., 2022a). On the other side, specific entry barriers are likely to work if the expected quality of touristic services in a given sub-

[4] To this extent, Appendix A1.1 shows the comparison between Airbnb and HomeAway supply and demand absolute numbers within the Italian market. As shown, Airbnb tent to outnumber HomeAway. Indeed, on average Airbnb stock is almost 3 times larger than HomeAway one, as well as reserved nights and reservations which are on average 5.43 and 7.62 larger, such that the assumption of monopolistic positioning of Airbnb can conservatively hold.
As reported in the Methodology section of this chapter, the separation between HomeAway and Airbnb will be exploited to build a BLP-like instrumental variables for the estimation of CNE.

market is high. To this extent, the share of *high-end* (four, five and five luxury starts) hotel beds, $PercLux_{pt}$, can be considered as an approximation of the costs in which an entering host incur when joining Airbnb given that the higher the share, the higher is the required minimum level of quality for accommodation services[5]. Second, the income level, proxying the general macroeconomic conditions of each sub-market, can play a crucial role in determining the decision to entry. Indeed, as long as sharing economy platforms act as additional/substitutive income providers (see Dogru et al., 2020 for a macroeconomic perspective on Airbnb diffusion), flourishing macroeconomic conditions (i.e., higher per capita GDP, $GDPc_{pt}$ as in the case of the paper, or similarly higher employment rates) can discourage people to join Airbnb because the opportunity costs of investing time and effort in sharing economy activities are significantly higher. Third, information and agglomeration effects are expected to affect the decision to enter the platform. Indeed, if on the one side information spreading through word-of-mouth effects can fulfill the diffusion of innovation (see for instance Bass, 1969), as long as more people join the platform producer side, clustering and competition effects are likely to exist. For instance, potential entrant may prefer to enter next to incumbents to enjoy proximity benefits (i.e., the sub-market can be more attractive to customers who have wider choices, Baum & Haveman, 1997), or, conversely, potential entrant may be discouraged if higher level of competition is present in a specific sub-market. In order to account for all these effects defining the utility function of potential entrants, in each sub-market *p* linear and quadratic terms of the number of months since the first Airbnb opening, MFF_{pt}, in the respective sub-market are included. Finally, in this empirical setting the fee P^{S}_{ipt} applied by Airbnb to potential suppliers can be assumed zero (i.e., the potential entrant is indifferent to that) given that the platform applies a variable percentage fee on each concluded reservation such that it can be covered by the contemporary income made through the reservation, and because the model assumes that Airbnb is a monopolistic platform within the market.

Under the assumption that utility in Equation 1.1. takes the functional form of a Cobb-Douglas (previously done in literature by Chu & Manchanda, 2016, and Rysman, 2004) it is possible to rewrite Eq. 1.1. as follows:

$$U^{S}_{itp} = \alpha + \beta \ln D_{tpk} + \gamma_1 AvgRent_{pt} + \gamma_2 PercLux_{pt} + \gamma_3 \ln GDPc_{pt} + \gamma_4 MFF_{pt} + \gamma_5 MFF^{2}_{pt} + \eta^{S}_{p} + \tau^{S}_{t} + \xi^{S}_{ipt} + \varepsilon^{S}_{ipt} \quad \text{(Eq. 1.2.)}$$

According to Eq. 1.2., the constant α captures the intrinsic preference for the platform while the coefficient β is the main parameter of interest because it captures the elasticity of supply-side utility to a variation of demand (i.e., cross-side externality, see Cabral, 2011). The coefficients γ_1 and γ_2 capture the elasticity of supply utility function with respect to the entry/opportunity costs conditions (long-term rental prices and share of high-end hotel beds), the coefficient γ_3 captures the elasticity of producers utility to macroeconomic factors variations proxied by the log of the income of the per capita GDP in sub-market *p*, γ_4 and γ_5 represent the elasticity of utility to information and agglomeration effects, and,

[5] The inclusion of the share of luxury hotels in the main costs item faced by potential Airbnb entrants, requires the assumption of complementarity between Airbnb and traditional accommodation. To this extent, this utility function embraces the point of view of Farronato & Fradkin (2022) who define Airbnb as a complementor of hotel supply, particularly in high demand periods.

finally, the coefficients η^{S}_{p} and τ^{S}_{t} capture the sub-market varying unobserved factors and time-varying ones affecting suppliers utility. In further econometric specifications of the model the coefficient β will be supposed to be sub-market varying according to the regional characteristics of the reference industry (i.e., hospitality), such that β_p coefficients will be estimated. Assuming the error term ε^{S}_{ipt} is independently and identically distributed (i.i.d.) with an Extreme Value Type 1 (EVT1) distribution[6] (Chu & Manchanda, 2016) it is possible to derive the probabilities of joining and not joining Airbnb supply side at time *t* in sub-market *p*, defining δ^{S}_{ipt} as in Equation 1.3.

$$\delta^{S}_{itp} = \alpha + \beta \ln D_{tpk} + \gamma_1 \mathrm{AvgRent}_{pt} + \gamma_2 \mathrm{PercLux}_{pt} + \gamma_3 \ln \mathrm{GDPc}_{pt} + \gamma_4 \mathrm{MFF}_{pt} + \gamma_5 MFF^2_{pt} + \eta^{S}_{p} + \tau^{S}_{t} + \xi^{S}_{ipt}$$

(Eq. 1.3.)

Following the procedure in Appendix A1.2. and assuming that the utility of not joining Airbnb is normalized to zero ($\delta^{S,\text{not join}}_{ipt}=0$) the probabilities of joining and not joining the platform are defined in Equation 1.4.:

$$\mathrm{PR}^{S,\mathrm{join}}_{ipt} = \frac{1}{1+e^{-(\delta^{S}_{ipt})}} = \frac{e^{\delta^{S}_{ipt}}}{1+e^{(\delta^{S}_{ipt})}}$$

$$\mathrm{PR}^{S,\mathrm{not\,join}}_{ipt} = 1 - \mathrm{PR}^{S,\mathrm{JOIN}}_{ipt} = \frac{1}{1+e^{(\delta^{S}_{ipt})}}$$

(Eq. 1.4.)

Under the assumption that multihoming of Airbnb listings is not allowed (see the introduction to Section 1.3), the probability of joining is equal to Airbnb's market share of entering listings over the total available market potential in a specific sub-market *p* at time *t*.

$$\mathrm{PR}^{S,\mathrm{join}}_{ipt} = \frac{n^{S}_{pt}}{M^{S}_{pt}} \qquad \mathrm{PR}^{S,\mathrm{not\,join}}_{ipt} = \frac{M^{S}_{pt} - n^{S}_{pt}}{M^{S}_{pt}}$$

$$\frac{\mathrm{PR}^{S,\mathrm{join}}_{pt}}{\mathrm{PR}^{S,\mathrm{not\,join}}_{pt}} = \frac{\dfrac{e^{\delta^{S}_{ipt}}}{1+e^{(\delta^{S}_{ipt})}}}{\dfrac{1}{1+e^{(\delta^{S}_{ipt})}}} = e^{\delta^{S}_{ipt}} = \frac{\dfrac{n^{S}_{pt}}{M^{S}_{pt}}}{\dfrac{M^{S}_{pt} - n^{S}_{pt}}{M^{S}_{pt}}}$$

(Eq. 1.5.)

Where n^{S}_{pt} is the number of new listings joining Airbnb at time *t* in sub-market *p*. M^{S}_{pt} is the theoretical market potential of sub-market *p* at time *t*. The market potential at time *t* is the potential number of house-buildings (i.e., dwellings or

[6] The peculiarity of the Extreme Value Type 1 distribution is its cumulative function which is in the following functional form:
$F(x) = 1/(1-e^{-x})$

residential type buildings) that can join Airbnb; thus, it is equal to the total number of empty Airbnb-style house-buildings before the beginnings of the diffusion of Airbnb, minus the active listings at *t-1*. Finally, the regression to be estimated is derived as follows in Equation 1.6.:

$$\ln\left(e^{\delta^{S}_{itp}}\right) = \ln\left(\frac{\frac{n^{S}_{tp}}{M^{S}_{tp}}}{\frac{M^{S}_{tp} - n^{S}_{tp}}{M^{S}_{tp}}}\right) = \delta^{S}_{itp}$$

$$= \alpha + \beta \ln D_{ptk} + \gamma_1 AvgRent_{pt} + \gamma_2 PercLux_{pt} + \gamma_3 \ln GDPc_{pt} + \gamma_4 MFF_{pt}$$

$$+ \gamma_5 MFF^2_{pt} + \eta^{S}_{p} + \tau^{S}_{t} + \xi^{S}_{ipt}$$

(Eq. 1.6.)

1.3.2. Consumers' Side (Demand, i.e., Visitors) Utility Model

The net indirect utility of a visitor *j* to use Airbnb at a specific time *t* in a given sub-market *p* can be synthetized by Equation 1.7.:

$$U^{D}_{jtp} = f(b^{D})\, f\left(S_{tp}, PV_{pt}, PI_{pt}, E_{pt}, X^{D}_{p}, X^{D}_{t}, \xi^{D}_{jpt}, \varepsilon^{D}_{jpt}\right) - P^{D}_{jtp}$$

(Eq. 1.7.)

As for the supply side, this utility is dependent on an intrinsic preference for the platform b^{D}, the stock of active listings on Airbnb in sub-market *p* at the moment of reservations *t* (referring to cross-side externalities), S_{pt}, the variety of offer present on the platform, PV_{pt}, the average price charged on the platform for an overnight stay, PI_{pt}. In line with Chu & Manchanda (2016), variety is a significant non-network factor predicting demand utility, since wider product offering incentivize the decision to consume on the platform marketplace. On the Airbnb side, variety can come in many forms, e.g., the share of entire apartment, or in a synthetic concentration indicator (i.e., HHI) measuring the market share of each listing typology as in Chu & Manchanda (2016). However, in line with the main selling/value proposition of Airbnb ('*find vacation rentals, cabins, beach houses, unique homes and experiences around the world - all made possible by hosts on Airbnb'* [7]), the share of particular listings $SharePart_{pt}$ in a specific sub-market *p* at time *t* can be considered as a good approximation of the variety of the offer determining visitors' utility[8]. The average price image PI_{pt} can be a significant indicator of the expected quality of touristic services offered by the platform, as well as a deterrent for specific customer segments. To this extent, the Average Daily Rate ADR_{pt} in a specific sub-marker *p* at time *t* can be considered representative of the average price level on the platform. Finally, the utility is dependent on the intrinsic touristic

[7] This aspect find its confirmation also on the newly designed homepage of Airbnb, which put on top te "wow" listings. Reference: https://www.airbnb.com

[8] Further clarification on the variable operationalization are in Section 1.4. (Data and Methodology).

attractiveness of a specific local sub-market *p* at a given time *t* (i.e., coastline sub-markets are, for instance, more attractive during summer seasons, or specific sub-markets host regular event every year in a specific period), E_{pt}, sub-market specific effects which do not vary over time X^{D}_{p} such as the presence of major touristic hotspots (i.e., monuments or natural attractions) which, in the same way of the supply side model, could affect also the stock of active properties in the respective sub-market p, seasonal factors X^{S}_{t}, other unobserved characteristics ξ^{D}_{jpt} and the fee applied by Airbnb per each reservation P^{D}_{jpt}. As for the supply side model, the fee P^{δ}_{itp} applied by Airbnb to each reservation can be assumed zero ($P^{D}_{jti} = 0$) such that the potential visitor is assumed to be indifferent to that[9].

Under the assumption that visitors' utility takes the functional form of a Cobb-Douglas it is possible to rewrite Eq. 1.7. as follows:

$$U^{D}_{jtp} = \lambda + \rho \ln S_{pt} + \varphi_1 SharePart_{pt} + \varphi_2 ADR_{pt} + \varphi_3 E_{pt} + \eta^{D}_{p} + \tau^{D}_{t} + \xi^{D}_{jtp} + \varepsilon^{D}_{jtp}$$

(Eq. 1.8.)

The constant λ captures the intrinsic preference for the platform of a visitor *j* while the coefficient ρ is the main parameter of interest because it captures the elasticity of demand-side utility to a variation of supply (i.e., cross-side externality). As for the supply-side model, in further econometric specification the coefficient ρ will be allowed to vary over sub-markets according to the regional (sub-market) industry structure of the hospitality industry in order to point out differentials in cross-side externalities according to regional varying factors. Finally, the coefficients φ capture the elasticity of demand to other non-network determinants: φ_1 capture the elasticity to the share of *particular* listings, φ_2 captures the elasticity of visitors to the average daily rate, while φ_3 depicts the relative contribution of market-season varying factors. Following the same methodological assumptions of section 1.3.1. (or, the explanation in Appendix A1.3.), the estimated demand equation is as follows, in Equation 1.9.:

$$\ln\left(e^{\delta^{D}_{jpt}}\right) = \ln\left(\frac{\frac{n^{D}_{pt}}{M^{D}_{pt}}}{\frac{M^{D}_{pt} - n^{D}_{pt}}{M^{D}_{tp}}}\right)$$

$$= \lambda + \rho \ln S_{pt} + \varphi_1 SharePart_{pt} + \varphi_2 ADR_{pt} + \varphi_3 E_{pt} + \eta^{D}_{p} + \tau^{D}_{t} + \xi^{D}_{jtp}$$

(Eq. 1.9.)

[9] According to Airbnb (2022), the pricing structure of the platform foresees that suppliers (i.e., hosts) are charged in general a percentage fee of about 3%, while visitors are charged on average a percentage fee varying about 14.2% per each reservation. Following the customer experience on the platform for an average visitor, it is worth to notice that the platform typically displays the whole price to the potential customer, while only at the moment of purchase the breakdown between services price and fees is shown. To this extent it is plausible to assume that the visitor can be indifferent to the fee.

Where, n^{D}_{pt} is the number of reservations on Airbnb at time *t* in sub-market *p*. M^{D}_{pt} is the theoretical market potential of sub-market *p* at time *t*. The market potential at time *t* the total number of reservations in the whole hospitality industry at time *t* in sub-market *p*.

1.4. Data and Methodology

This section shows the data sources employed to estimate the theoretical model shown in Section 1.3., as well as the methodologies and the operationalization of the variables used in the econometric models.

1.4.1. Data Sources

This study primary relies on the commercial dataset furnished by AirDNA, a leading provider of short-term rental data (https://www.airdna.co), which contains Airbnb listing-level information of the whole Italian market. In particular, the dataset provides both supply side (since Airbnb inception in Italy, i.e., 2008) and demand side information (since 2017). On the one hand, per each listing on the platform the dataset contains the listing typology, the Creation Date (i.e., the date in which the listing has joined the platform) and the Last Active Date (i.e., the date in which the listing has left the platform), such that it is possible to draw per each interval of time *t* the number of new joining listings Airbnb and the stock of active properties. According to the geo-localization of each listing (i.e., latitude and longitude), data have been aggregated at a sub-market level. On the other hand, the dataset contains information on the reservations received by each listing at time *t* (as well as other performance metrics such as reserved nights and monthly revenues), such that per each time interval *t* and sub-market *p* the total number of reservations (i.e., demand) can be calculated. For the purpose of the analysis, a NUTS3 region (i.e., province) is considered a specific sub-market *p*. Despite multiple geographic aggregations can be adopted in the analysis, either more granular (i.e., LLMA or municipalities) or more aggregated (i.e., NUTS2), the NUTS3 level is assumed to be a functional geographic aggregation because the demand between different NUTS3 can be considered separated (while, for instance, demand for different municipalities cannot be considered independent, in particular in rural markets)[10]. Furthermore, the majority of the control variables adopted in the econometric equations are available at the NUTS3 level. In order to have similarity between demand and supply data, the final panel dataset is structured over 105 different panels (i.e., provinces) and 36 time intervals (month of the year, from January 2017 to December 2019).

[Insert Figure 1.1. here]

Figure 1.1. shows the Airbnb supply side (Fig. 1.1A) and demand side evolutions (Fig. 1.1B). Both charts confirm the presence of a strong seasonal component into the entries on Airbnb supply side and into demand for Airbnb services. Furthermore, the seasonal peaks of Airbnb entries slightly anticipate the peaks of demand (which usually happen during

[10] Eventual spatial autocorrelations of Airbnb presence between different NUTS3 can be attributable to similar morphological aspects of contiguous sub-markets influencing the variations in demand and supply. By the means of fixed effects model, the econometric specification will control for this aspect.

the summer season on August), suggesting further methodological steps which has to be considered when defining the demand variable to be included into the supply equation. The evolution of the supply side follows a similar-logistic curve closer to the maturity stage of diffusion (as expected in the diffusion of innovative products, see Bass, 1969), such that new entries are firstly increasing and then decreasing.

Finally, further data are derived from public data sources such as ISTAT (the Italian National Institute of Statistics[11]) for sub-market level variables including the supply-side and demand side market potentials, the provincial per capita GDP and the industry structure at the local level. Finally, from the Observatory of the Italian Real Estate Market[12], owned by the Italian Revenue Agency, data on the average long-term rental prices are downloaded.

1.4.2. Variables Operationalization

1.4.2.1. Producers (Supply) and Consumers (Demand) Utility

According to Equations 1.6. and 1.9., the utility of joining Airbnb supply side and using Airbnb services to reserve an overnight stay side are calculated as follows:

$$\delta^{S}_{ipt} = \ln\left(\frac{\frac{n^{S}_{pt}}{M^{S}_{pt}}}{\frac{M^{S}_{pt} - n^{S}_{pt}}{M^{S}_{pt}}}\right) = \ln\left(\frac{n^{S}_{pt}}{M^{S}_{pt} - n^{S}_{pt}}\right) \qquad \delta^{D}_{jpt} = \ln\left(\frac{\frac{n^{D}_{pt}}{M^{D}_{pt}}}{\frac{M^{D}_{pt} - n^{D}_{pt}}{M^{D}_{pt}}}\right) = \ln\left(\frac{n^{D}_{pt}}{M^{D}_{pt} - n^{D}_{pt}}\right)$$

(Eq. 1.10.)

The utility of joining Airbnb supply side is computed as the log of the ratio between the probability of joining to the probability of not joining, deriving from the variables n^{S}_{tp} and M^{S}_{pt}. The first variable represents the number of new Airbnb listings in sub-market *p* at time *t* and is computed as the number of listings geo-located in NUTS3 *p* which have a Creation Date equals to *t*. M^{s}_{pt} represents the dynamic market potentials of new suppliers entrants, i.e., the theoretical maximum number of new entrants in sub-market *p* at time *t*. M^{s}_{pt} is calculated as the difference between the stock of unoccupied dwellings in sub-market *p* at the national survey in 2011 (i.e., the latest available census; the method can conservatively assumes that this survey is before the entry or the major diffusion of Airbnb in the majority of the Italian provinces) minus the stock of active Airbnb at *t-1*. Given that monthly level data on the stock of unoccupied dwellings at NUTS3 level are not available, the approximation of the market potential M^{s}_{pt} is the most feasible one, also assuming that no other options are allowed to potential entrants to exploit the real estate capital, as explained at the beginning of Section 1.3.

The utility of using Airbnb reserving a stay on Airbnb side is computed as the log of the ratio between the probability of reserving a stay on Airbnb to the probability of not doing it, deriving from the variables n^{D}_{pt} and M^{D}_{pt}. The variable n^{D}_{pt} counts the total number of reservations in sub-market *p* at time *t*, while the dynamic market potential (M^{D}_{pt}) is derived

[11] Website: https://www.istat.it
[12] Website: https://www.agenziaentrate.gov.it/portale/web/guest/aree-tematiche/osservatorio-del-mercato-immobiliare-omi

from ISTAT databases as it is the global touristic demand (thus also including for instance reservations in hotels and similar accommodations) in NUTS3 *p* at time *t*.

[Insert Figure 1.2. here]

Figure 1.2. shows the Italian average utilities evolution over time, either comparing them in absolute values (Fig. 1.2A) or in relative term (Fig. 1.2B) by rescaling the mean utility to the starting value at January 2017. The utilities plotted are an average over the whole Italian territory[13]. As for the charts in Figure 1, the seasonal component is evident depicting positive and negative peaks over time. According to Fig. 1.2A, the utility of using Airbnb services on the demand side is increasing over time, while the utility of joining Airbnb supply side is rather stable and then decreasing at the end of the observation period, as argued when discussing the presence of competition effects deriving from agglomeration forces.

It is worth to notice that the utility-based approach has the advantage of relying on shares (of both entrants and demand) rather than on absolute values. Under the methodological point of view this approach is useful because, after proper computation, the demand to supply and supply to demand elasticities will be compared by calculating the impact on the share of potential entrants or share of demand.

1.4.2.2. CNE Variables: Demand and Stock of Active Listings

The demand for Airbnb services faced by potential entrants on Airbnb supply side, which allows our model to estimate the demand to supply cross side externalities, has been operationalized taking into account that prospective entrants i) take care of future return expected when joining Airbnb, ii) the performances of the platform until the moment of the decision. To this extent, the decision to join Airbnb has to consider not only the present value of demand, but also future and past lags of the variable given that the host has expectations over the future moths and carefully evaluate the former performances of the platform in the past. According to this premise, the demand variable D_{ptk} is defined as follows:

$$\mathrm{D_{ptk}} = \sum_{\Gamma=0}^{\Gamma=t+k} \mathrm{ResNights_{p\Gamma}}$$

(Eq. 1.11)

Where $\mathrm{ResNights_{p\Gamma}}$ is the number of reserved nights in sub-market *p* at time Γ and k is the number of months ahead of t of interest to the potential entrant. The main estimates will adopt k equals to 3 because on average three quarter of the reservations are done up to three months before the overnight stay[14]. Thus, as reported in Eq. 11, the demand variable estimating the demand to supply elasticities, is the cumulative sum of reservations up to three months ahead of the time t. In the econometric model the variable has been log-transformed.

[13] The utility takes negative values because it is the log of a ratio which is by definition lower that 1, given that in almost all cases (but not all ones), the share of Airbnb supply/demand is lower than the share of the alternative options.

[14] These statistics are derived by the author from AirDNA data. Further clarification and other descriptive statistics are available upon requests to the author.

The stock of active Airbnbs, $StockAirbnb_{pt}$, available at time *t*, influencing the utility of reserving on Airbnb (demand side utility), is computed as follows. Similar to the demand variable, also this metric has been log transformed.

$$\mathrm{StockAirbnb_{pt}} = \mathrm{StockAirbnb_{pt-1}} + \mathrm{NewAirbnb_{pt}} - \mathrm{ExitAirbnb_{pt}}$$

(Eq. 1.12)

Appendix A1.4. shows the univariate association between the utility of joining Airbnb supply side to the respective demand faced by the potential entrant and the utility of reserving a stay on Airbnb to the actual supply. Both charts show that, according to the expectations, positive cross side externalities exist on the Airbnb platform given the two positive slopes in both scatter plots.

1.4.2.3. Non-Network Factors

As reported in the theoretical model, average long-term rental prices and the share of high-end hotel bed places are intended as entry/opportunity costs faced by prospective entrants on Airbnb supply side. The first variable has been operationalized taking the averages of the minimum and maximum rents (in euros per squared-meter per month) in sub-market *p* of Airbnb-style facilities (i.e., all business-type facilities have been excluded) at time *t*, furnished by the Italian Observatory of the Real Estate Market. The variable $AvgRent_{pt}$ employed in the model is the mean value between the minimum and the maximum one. It is worth noting that these data are semesterly released, thus the variable varies between panels but only semesterly within time. The variable depicting the share of high-end hotel bed places, $ShareLux_{pt}$, is derived from ISTAT database, it is released yearly at the panel level (province). The variable is computed as the ratio of the bed in four, five and five luxury star hotels over the total number of hotel bed places. General income levels affecting the decision of potential suppliers are derived from ISTAT database too and are operationalized as the yearly per capita GDP at the NUTS3 level, namely the variable $GDPc_{pt}$. Agglomeration and work-of-mouth effects are proxied by the number of months (in linear and quadratic term) from the first Airbnb opening in a sub-market *p,* i.e., the variables MFF_{pt} and MFF^2_{pt} (to this extent, the variables varies between panels and months).

Potential visitors' decision to reserve a stay on Airbnb is shaped by the variety of *particular* accommodation in each sub-market at each time interval and by the average price image. The first variable, $SharePart_{pt}$, is computed by taking the ratio of particular property types over the whole active properties in sub-market *p* at time *t.* A listing is defined as *particular* if it falls among the following categories: Villa, Boat, Auto, or other micro-categories (e.g., farm, treehouse). The price image is represented by the Average Daily Rate in sub-market *p* at time *t*, ADR_{pt}, is computed as the total revenues divided by the reserved nights. As commonly used in the tourism literature (e.g., Sainaghi et al., 2021), the variable approximates the general price level of the platform. Finally, the theoretical model postulates the share of reservations on the platform in a sub-market *p* at time *t* is dependent on the intrinsic touristic attractiveness of a specific local sub-market *p* at a given time *t*, E_{pt}. This attractiveness be for instance the presence of natural amenities whose value changes over seasons (i.e., demand peaks are expected to occur during winter in the northern region of Italy, while during summer in southern regions), or recurring events which attract larger fluxes of tourists in a given market every year. To this extent, as

approximation of these factors, a set of dummies identifying a pair NUTS2 – Quarter of the year is introduced to proxy the variable E_{pt}.

1.4.3. Econometric Model

Two equations are estimated in order to determine the cross-side externalities on Airbnb platform. The baseline models are directly derived from the theoretical models explained in Section 1.3., equations 1.6. and 1.9.:

$$\ln\left(e^{\delta^{S}_{itp}}\right) = \ln\left(\frac{\frac{n^{S}_{tp}}{M^{S}_{tp}}}{\frac{M^{S}_{tp} - n^{S}_{tp}}{M^{S}_{tp}}}\right) = \delta^{S}_{itp}$$
$$= \alpha + \beta \ln D_{ptk} + \gamma_1 AvgRent_{pt} + \gamma_2 PercLux_{pt} + \gamma_3 \ln GDPc_{pt} + \gamma_4 MFF_{pt}$$
$$+ \gamma_5 MFF^2_{pt} + \eta^{S}_{p} + \tau^{S}_{t} + \xi^{S}_{ipt}$$

(Eq. 1.6.)

$$\ln\left(e^{\delta^{D}_{jpt}}\right) = \ln\left(\frac{\frac{n^{D}_{pt}}{M^{D}_{pt}}}{\frac{M^{D}_{pt} - n^{D}_{pt}}{M^{D}_{tp}}}\right)$$
$$= \lambda + \rho \ln S_{pt} + \varphi_1 SharePart_{pt} + \varphi_2 ADR_{pt} + \varphi_3 E_{pt} + \eta^{D}_{p} + \tau^{D}_{t} + \xi^{D}_{jtp}$$

(Eq. 1.9.)

In both equations the estimation of the cross-side elasticity (coefficients β and ρ) is straightforward because omitted variable biases resulting in endogeneity problems are likely to arise. To deal with these issues, several steps have been followed in the analysis to rule out the effect of demand on suppliers' utility and supply on visitors' utility. First, the inclusion on non-network factors into supply and demand equation controls for multiple sources of variation of our dependent variable. For instance, the inclusion of the variables MFF_{pt} and MFF^2_{pt} allows the supply model to control for the stage of diffusion of Airbnb into the sub-market, which is expected to be correlated with both demand (i.e., it is reasonable to assume that the longer the diffusion, the higher is the demand) and the utility of joining Airbnb by the means of information and agglomeration mechanisms as reported in section 1.3. To this extent, the CNE estimate of β can be intended cœteris paribus the penetration of the platform into the local market. Second, the panel data structure of the dataset allows to introduce the individual fixed effects η^{S}_{p} and η^{D}_{p} and time-specific controls τ^{S}_{t} and τ^{D}_{t} (i.e., month of the year dummies to consider seasonal patterns into the data, see Figure 1.1.). To this extent, the adoption of a fixed effects model is crucial because it controls for possible omitted variable biases (resulting in co-determination issues) between regressors and individual unobserved characteristics that are time-invariant. For example: a) both demand for

Airbnb services and utility of joining Airbnb supply side can be explained by the touristic attractiveness of the sub-market *p* (similarly for the demand side model) which can be conservatively assumed to be static over time and unobserved at the individual level, or b) either demand and utility may be both dependent on the period of the year, thus the correction for month of the year dummies is necessary to control for seasonality within data. The Hausman Test has been performed before running the regression models, confirming the adoption of a fixed effects model rather than a random effects one.

1.4.3.1. Instrumental Variable

Despite the inclusion of fixed effects and control variables, which can rule out multiple causes of endogeneity, it is likely that omitted variable biases can still arise because market-time varying unobserved characteristics, correlated with both supply and demand, are likely to be not included into the model. For instance, this can be the case of specific shocks occurring at the sub-market level such as a marketing campaign promoted by Airbnb which can influence both supply and demand. The best approach to deal with this issue is to further include instrumental variables that affect the endogenous regressors (D_{ptk} and S_{pt}). To the extent that in further econometric models, the CNEs β and ρ will be allowed to vary over sub-markets *p*, it is worth to notice that the instrumental variables required for the analysis need to vary over market and time jointly[15].

In line with these arguments, the analysis uses the following BLP-like instrumental variables, relying on the availability of data on the diffusion and usage of the platform HomeAway at the same geographical and time units. In particular, the stock of active listings on HomeAway platform, Sha_{pt}, has been used to instrument the stock of active listings on Airbnb in Eq. 1.9., and the number of reservations, Dha_{ptk} (operationalized in the same way of the variable D_{ptk}), has been employed to instrument demand in Eq. 1.6.. The intuition on the usage of the instrument relies on the degree of substitution and complementarity of the platforms. If, for instance, Airbnb and HomeAway would be perfect substitutes, the instrumental variable would be invalid because unobserved variables would be still correlated with the endogenous variables in the model. However, there are some arguments such that both platforms can be considered complementors rather than substitutes. First, the two platforms have historical differences and different value propositions to their customers. Indeed, if on the one side HomeAway has historically focused on vacation rentals of entire homes only on vacation rental places (Farronato & Fradkin, 2022), Airbnb has normally not been such selective being its mission claiming '*Stay in a home away from home wherever you travel*'[16]. Furthermore, as shown in Table 1, quantitative arguments are in support of this hypothesis. Indeed, in line with the value propositions of both platforms, HomeAway tend to be located

[15] In this case, the adoption of shift-share instruments as previously used into the Airbnb literature (Garcia Lopez et al., 2020) to estimate supply-side diffusion is not possible because this instrumental variable approach assumes a common *velocity* of diffusion over all panels as the share component does only vary over time and not across panels also (for instance, Garcia-Lopez et al., 2020, use the Google search index for '*Airbnb*' as share component in their analysis).

[16] Further clarifications here: https://digital.hbs.edu/platform-digit/submission/airbnb-stay-in-a-home-away-from-home-wherever-you-travel/.
It is of course plausible that Airbnb supply and demand may tend to co-locate with HomeAway one because the higher the touristic attractiveness, the higher the supply and demand penetration will be. However, we can conservatively assume that such touristic attractiveness can be strictly dependent on time-unvarying variables within our dataset, in particular our time interval (e.g., the presence of natural amenities or other specific touristic trends which are not expected to change within our dataset).

on a different market segment, addressing visitors looking for longer stays and, on average, with higher willingness to pay.

[Insert Table 1.1. here]

In order to incorporate the instrumental variables within the econometric estimates, the two-stage control function approach has been used (Petrin & Train, 2010; Chu & Manchanda, 2016). First, the variable D_{ptk} has been regressed on the variable Dha_{ptk} (i.e., the same operationalization of demand, using data from HomeAway platform) and all the other explanatory variables in Eq. 1.6., including individual and month-of-year fixed effects also, and residuals r^{D}_{ptk} have been computed. Second, the variable S_{pt} has been regressed on the stock of active listings on HomeAway platform Sha_{pt} and all other explanatory variables in Eq. 1.9. (including all fixed effects), and then residuals r^{S}_{pt} have been computed. Finally, residuals r^{D}_{ptk} and r^{S}_{pt} have been included respectively into Eq. 1.6. and Eq. 1.9., using either linear or quadratic terms into the control function. Appendix A1.5. shows the results of the first stage regressions, Appendix A1.6. shows the main descriptive statistics of both r^{D}_{ptk} and r^{S}_{pt}. It is worth to notice that, after estimating the classical 2SLS approach, the Kleibergen-Paap tests are fully fulfilled, such that the instruments are strong enough to predict the endogenous explanatory variable.

1.4.3.2. Simultaneity & Common Shocks

In this empirical setting there is the potential issue of simultaneity, such that it is straightforward to rule out which side of the platform affect the other. In order to control for simultaneity issues, the empirical models use excluded variables (Chu & Manchanda, 2016) to estimate both equations. In particular, while entry/opportunity costs, average income level and word-of-mouth/agglomeration effects do only affect suppliers' utility function, the share on particular listings, the average price level and the market-season varying factors do only affect visitors' one.

Furthermore, since it is plausible that both equations can experience common shocks, the model will be also tested, as robustness check, by the means of a Seemingly Unrelated Equation (SUREG) approach (Srivastava & Dwivedi, 1979), such that the error term of both equations will be allowed to be correlated.

1.4.3.3. Space (Sub-Market) Varying CNE

In order to disentangle differentials in the cross-side externalities according to specific sub-market level industry characteristics, the following additional specification of the models have been estimated (Eq. 1.12. and 1.13.):

$$\ln\left(e^{\delta^{S}_{itp}}\right) = \ln\left(\frac{\frac{n^{S}_{tp}}{M^{S}_{tp}}}{\frac{M^{S}_{tp} - n^{S}_{tp}}{M^{S}_{tp}}}\right) = \delta^{S}_{itp}$$

$$= \alpha + \beta \ln D_{ptk} + \beta^{SI} \ln D_{ptk} * SI_{p} + \beta^{DI} \ln D_{ptk} * DI_{p} + \gamma_{1} AvgRent_{pt} + \gamma_{2} PercLux_{pt}$$

$$+ \gamma_{3} \ln GDPc_{pt} + \gamma_{4} MFF_{pt} + \gamma_{5} MFF^{2}_{pt} + \eta^{S}_{p} + \tau^{S}_{t} + \xi^{S}_{ipt}$$

(Eq. 1.12.)

$$\ln\left(e^{\delta^{D}_{jpt}}\right) = \ln\left(\frac{\frac{n^{D}_{pt}}{M^{D}_{pt}}}{\frac{M^{D}_{pt} - n^{D}_{pt}}{M^{D}_{tp}}}\right)$$

$$= \lambda + \rho \ln S_{pt} + \rho^{SI} \ln S_{pt} * SI_{p} + \rho^{DI} \ln S_{pt} * DI_{p} + \varphi_{1} SharePart_{pt} + \varphi_{2} ADR_{pt}$$

$$+ \varphi_{3} E_{pt} + \eta^{D}_{p} + \tau^{D}_{t} + \xi^{D}_{jtp}$$

(Eq. 1.13.)

According to Eq. 1.12 and 1.13., the econometric specification assumes that there is a common cross side externality to all sub-markets *p* (β and ρ), while specific variations occur according to the industry structure of a market *p*, as proxied by the means of the variables SI_p and DI_p, respectively representing the intensity of supply within the touristic industry, and touristic appeal of the local sub-market.

The variables are drawn upon the report provided by ISTAT on the classification of all Italian municipalities according to the touristic density[17]. The report provides per each Italian municipality two synthetic indicators describing the supply intensity[18] and the demand intensity[19] of the whole local touristic industry in five-level categorical variable (with values ranging from 1 to 5). Data at the municipal level provided by the report have been aggregated at the sub-market *p* level taking the share of the population living in municipalities classified as mid-high/high (level 4 and 5 of the five-level categorical classification) supply intensity and demand intensity over the total population of the respective NUTS3. To this extent, the variables SI_p and DI_p are defined. SI_p measures the share of population in sub-market *p* living in municipalities with mid-high/high supply intensity, and account for multiple factors which can have influence on CNE such as the thickness of competition with other touristic services on the supply side, or the number of alternative options faced by visitors when making a reservation in a given sub-market. DI_p, instead, is defined as the share of population in sub-market *p* living in municipalities with mid-high/high demand intensity and classifies each sub-market according to the touristic appeal, which can have impact on CNE. To the extent that the intensity of cross-side externalities may vary over time starting from the 'launch' of the platform (Chu & Manchanda, 2016), it is worth to notice that no correlation exists between the variables SI_p and DI_p with the number of months from the entry of the first supplier into the corresponding sub-market *p*.

[17] Link: https://www.istat.it/it/files//2020/09/classificazione-turistica-comuni.Istat_.pdf. The analysis has been conducted with data before the Pandemic outbreak. Furthermore, given that the analysis aims at distinguishing municipalities according to the global touristic industry structure, this analysis can conservatively assume that the classification provided with data in 2019 are valid even for 2017 and 2018.

[18] Supply intensity is measured as a synthetic indicator accounting for: total hospitality rate, total hospitality density, high-end hospitality rate, extra traditional hospitality rate and municipality hospitality penetration rate. The operationalization of all variables is explained in the report (see footnote 18).

[19] Demand intensity is measured as a synthetic indicator accounting for: touristic pressure, outbound touristic pressure, inbound touristic pressure, average global occupation rate, average total length of stay, seasonality indicator, municipality concentration indicator, touristic demand density and museums' visitors pressure indicator. The operationalization of all variables is explained in the report (see footnote 18).

1.4.3.4. Computation of CNE & Elasticities

Following Chu & Manchanda (2016) and Gandal et al. (2000), relying on the estimation of the parameters, it is necessary to compute elasticities in order to retrieve comparable values. Starting from Eq. 1.6 and 1.9, the average CNE are computed as follows:

$$\mathrm{CNE}_{\mathrm{D2S}} = \beta * (1 - \mathrm{PR}^{\mathrm{S,join}})$$

$$\mathrm{CNE}_{\mathrm{S2D}} = \rho * (1 - \mathrm{PR}^{\mathrm{D,use}})$$

(Eq. 1.14.)

Where $PR^{S,join}$ is the market share of suppliers' entrant and $PR^{D,use}$ is the share of demand captured by Airbnb (i.e., the probability of reserving a stay on Airbnb). Both shares have been introduced at the mean value and multiple percentiles to estimate CNE at different values of market shares. To this extent, the values CNE_{D2S} and CNE_{S2D} can be interpreted as the percentage increase of supply or demand shares associated with a percentage increase of demand or supply at the mean (or other values) of supply or demand shares.

When CNE will be allowed to vary over sub-market characteristics according to the variables SI_p and DI_p, the CNE are computed as follows:

$$\mathrm{CNE}^{\mathrm{SI}}_{\mathrm{D2S}} = (\beta + \beta^{\mathrm{SI}} * \mathrm{SI}) * (1 - \mathrm{PR}^{\mathrm{S,join}})$$

$$\mathrm{CNE}^{\mathrm{DI}}_{\mathrm{D2S}} = (\beta + \beta^{\mathrm{DI}} * \mathrm{DI}) * (1 - \mathrm{PR}^{\mathrm{S,join}})$$

$$\mathrm{CNE}^{\mathrm{SI}}_{\mathrm{S2D}} = (\rho + \rho^{\mathrm{SI}} * \mathrm{SI}) * (1 - \mathrm{PR}^{\mathrm{D,use}})$$

$$\mathrm{CNE}^{\mathrm{DI}}_{\mathrm{S2D}} = (\rho + \rho^{\mathrm{DI}} * \mathrm{DI}) * (1 - \mathrm{PR}^{\mathrm{D,use}})$$

(Eq. 1.15.)

Such that the CNE will be evaluated at multiple values of SI_p and DI_p[20].

1.5. Results

This section provides the results quantifying the cross-side network externalities on Airbnb platform, showing the presence of differentials in externalities according to sub-markets' characteristics and, finally, providing a simulation study which largely draws on the main findings of the research. Throughout the entire results' discussion, robustness checks and alternative estimation methods will be presented. Table 1.2. sums up the main variables employed in the model, as well

[20] The analysis is interested in computing the S2D and D2S elasticities at:

a) different marginal levels of SI, regardless the level of DI, still with the coefficient β^{DI} coeteris paribus the demand intensity DI.
b) different marginal levels of DI, regardless the level of SI, still with the coefficient β^{SI} coeteris paribus the demand intensity SI.

as providing the summary statistics per each of them. Appendix A1.7. shows the correlation matrix between regressors for both demand and supply equations.

[Insert Table 1.2. here]

1.5.1. Baseline Model: Estimate of CNE

Tables 1.3. and 1.4. show the estimates of the baseline Eq. 1.6. and Eq. 1.9. All estimates have been computed by the means of Stata 17, employing clustered robust standard errors. Models M1 to M5 in both Tables 1.3. and 1.4. use standard OLS, while models M6 and M7 use the two-stage approach with control function. Appendixes 8 and 9 show respectively the regression diagnostic charts for supply and demand model.

[Insert Table 1.3. here]

[Insert Table 1.4. here]

Both models show that, as ex-ante expected, cross side externalities are likely to exist on Airbnb. Both coefficients β and ρ are indeed significant at 99.9% confidence level (excluding β in model M7 in Table 3, significant at 99% confidence). Further discussion on the marginal effects will be discussed later. The contribution of CNE to the explained variance is remarkable, being the overall R2 sharply increasing when switching from M4 to M5 in both Table 3 and 4. Furthermore, also the information criterions AIC and BIC confirm this insight, being the corresponding value significantly lower in models including the CNE term. Also, some non-network factors play a significant role in determining suppliers' or visitors' utility.

In particular, the average long term rental prices are negatively associated with the entries on Airbnb supply side, confirming the ex-ante expectations being long-term rentals perceived as entry/opportunity costs because of the substitutivity between short-term rentals and long-term ones. A unit increase in the average long-term rental price, indeed, is associated with a 1.15% decrease of the share of new entrants (at the mean value)[21]. The marginal effect of the other cost item, $PercLux_{pt}$, included into the supply equation is not significantly from zero, suggesting that the expected quality of touristic services do not impact suppliers' decision. After controlling for demand level and time from local Airbnb diffusion begin, the local per capita GDP is negatively correlated with suppliers' entries, suggesting that where the economy is flourishing, the utility of exploiting Airbnb services is lower because alternative ways to employ capital and effort are more remunerative. The time from local Airbnb diffusion begin is negatively correlated with the entries of suppliers. As long as the panel starts in 2017 (almost 9 years after the first Airbnb entry in Italy), the finding can be interpreted as a first signal of supply-side saturation.

On the demand side, the share of particular listings is strongly significant and positively correlated with Airbnb demand market shares. In particular, when the share of particular listings increases by 1% from the mean value, the average

[21] The marginal effect is computed according to M6 in Table 1.3.

share of Airbnb demand increases by 1.83%[22]. The general price level has a positive, still weakly significant, impact on Airbnb demand shares, suggesting that, in this case, price is likely to act a quality signal.

[Insert Table 1.5. here]

Table 1.5. shows the elasticities computed starting from models M6 in Tables 1.3. and 1.4. Demand to Supply elasticities (D2S) are derived from the estimation of β, while Supply to Demand elasticities (S2D) are derived from the estimation of ρ. The model shows that the intensity of CNE on Airbnb is significantly different. Indeed, if on the one side a percentage increase in Airbnb demand increases the average share of entrant suppliers by 0.769%, on the other side, a percentage increase in the stock of active properties icreases the average share of suppliers' entrants by 4.615%, pointing out that S2D externalities are, on average, six times larger than D2S ones (it is worth to notice that Chu & Manchanda, 2016, found that on the e-commerce platform Taobao, S2D externalities are 4 times larger than D2S ones). Following the main literature on multi-sided platforms strategic management (e.g., Parker & Van Alstyne, 2005), Table 1.5. allows predict the presence of a *subsidy-side* into the Airbnb platform that is the supply one given that the stronger externalities are generated from supply to demand rather than from demand to supply, namely suggesting that the growth of Airbnb is primarily supply driven. The insight is rather interesting, also in relation to the strategies employed by Airbnb when facing the Covid-19 shock. Indeed, as long as that the Pandemic caused an exogenous shock on the demand side, constraining the international (and sometimes national) mobility of travelers (Hu et al., 2020), it is worth to notice that one of the main strategic actions taken by the platform during such period has been the opening of a hosts' reimbursement fund of about M$250 to help hosts facing rising cancellations and reimbursement requests[23]. In the light of the finding of this paper, the platform has been straightforward and, particularly, forward looking, given that it has been able to recognize the importance of the stock of active properties on the long-term growth of the market, rather than focusing only on the directly impacted demand.

1.5.1.1. Robustness Checks

To the extent that the estimates are based on multiple theoretical and empirical assumptions, a wide set of robustness checks is proposed.

First, concerning the simultaneity problems and the possibility of allowing common shocks to both equations, a SURE approach has been employed. In particular, rather than estimating two separated equations, both equations have been jointly estimated, allowing the error terms to be correlated. Results, employing a linear control function are available in Appendix A1.10, and show comparable estimates, in terms of both magnitude and statistical significance to those reported in Tables 1.3. and 1.4., either for the main explanatory variables (D_{ptk} and S_{pt}) and the other non-network variables. Only the impact of the general price level becomes a not significant predictor of visitors' utility.

[22] The marginal effect is computed according to M6 in Table 1.4.
[23] A detailed press article is available here: https://www.reuters.com/article/us-health-coronavirus-airbnb-idUSKBN21H3GD

Second, to the extent that the model largely uses cumulative data (i.e., the demand into the supply equation and the stock of active properties into the demand equation), it is worth to test the sensitivity of the results using an autoregressive order one, AR(1), error structure. Results of the supply equation are in Appendix A1.11, while those of the demand equation are in Appendix A1.12. Results are comparable in terms of magnitude and significance of the estimated coefficients. Only the $AvgRent_{pt}$ becomes a not significant predictor of entrant suppliers' utility, still this can be caused by the fact that the variable does vary over semester, while panel time indicator is monthly.

Third, it is plausible that the market potential for prospective suppliers is overestimated given that it can incorporate dwellings which are not suitable for Airbnb or just because they are not empty at the beginning of the sample period (remember that the market potential has been derived from the national census in 2011, while the analysis starts in 2017). To this extent, the supply model has been tested using a fraction of the unoccupied dwellings as starting value for the computation of the dynamic market potential. Appendix A1.13 shows the results using the 50% of $\mathbf{M}_{\mathbf{tp}}^{\mathbf{S}}$ at the beginning of the sample period, while Appendix A1.14 shows the estimates using 60% of $\mathbf{M}_{\mathbf{tp}}^{\mathbf{S}}$. Results are rather comparable.

1.5.2. Spatial (Sub-Market) Varying CNE Estimate

If Equations 1.6. and 1.9. do assume that CNE are not varying over sub-markets, this section aims to provide a novel insight to the definition of network externalities studying geographically separated multi-sided platforms. To this extent, Eq. 1.12. and 1.13. have been estimated, thus predicting the CNE at different values of the main variables defining the local industry structure (in this case the touristic one).

[Insert Table 1.6. here]

[Insert Figure 1.3. here]

Table 1.6. shows the D2S and S2D elasticities at different values of SI_p and DI_p, computed according to Eq. 15, and Figure 1.3. plots the respective confidence intervals for the sake of comparison. Appendix A1.15 shows the full regression output of the estimation of the modified supply model, and Appendix A1.16 shows the output of the estimated modified demand model using a liner control function. Robustness checks with standard OLS and quadratic control functions have been tested with similar results. Furthermore, results are robust when including separately or jointly the local sub-market variations of CNE. This is particularly important because the aim of the analysis is to find out variations of CNE according to supply or demand industry structure, cœteris paribus the other one. Different insights are found. On the one side D2S externalities are not significantly varying over local market characteristics. In order words, prospective entrant hosts perceive demand variations regardless the intensity of supply-side competition (as proxied by SI_p), or the local market touristic appeal (proxied by DI_p). On the other hand, S2D externalities are much more sensitive to the local industry structure. In particular, S2D externalities are much stronger when SI_p is higher, or when DI_p is lower. The interpretation of results is as follows.

First, when the supply intensity indicator (SI_p) is higher, the competition faced by Airbnb with substitute services (i.e., traditional hospitality structures, family-managed b&b working with different sales channels) gets to increase, such that the models predicts that increases in the installed base of suppliers are able to generate stronger incentives to potential visitors to reserve a stay on the platform. In other words, in such cases potential visitors do care even more about the stock of active listings on the platform because they can enjoy: i) wider variety of choices, in the sense of facing multiple alternative accommodation solutions[24], ii) increasing peer-supply competition which has a direct impact on the quality and on the services proposed by Airbnb hosts[25]. On the other side, when the intensity of supply competition is lower, the general degree of choices faced by potential visitors is lower, such that the marginal effect of an additional listing adds less value to visitors. Second, when the local demand intensity indicator (DI_p) is lower, such that the general *demand* appeal of the touristic market is lower, marginal increases in the stock of active properties generate stronger incentives to potential visitors when compared to local markets with higher demand appeal. This result shows that the platform, in condition of lower demand appeal, can act as accelerator of demand-growing processes, such that even minimum increases of the producers' stock can generate stronger impact on the demand for the platform services. This is because, cœteris paribus, demand can be less intense because of the lack of specific touristic services which can be covered by the platform producers.

These results provide novel insights to the definition of CNE in multi-sided markets. Indeed, following the main definition of Katz & Shapiro (1994), and further studies, such a Chu & Manchanda (2016), who provided a time-varying characterization on the economic phenomenon, the paper shows that in multi-sided markets characterized by a strong geographical component, CNE do vary also over space, according to local sub-market industry characteristics. The results are likely to derive implications for managerial concerns regarding MSM business models. For instance, to the extent that the chicken-egg problem (Caillaud & Jullien, 2003) is widely recognized as one of the biggest challenges in MSMs (Cusumano et al., 2020), recognizing the differentials in elasticities according to the different local conditions can be an efficient way to overcome potential start-up failures, especially for platforms like Airbnb or Uber (characterized by a geographical separation of markets) facing multiple chicken-egg problems over the platform life because they have to penetrate multiple local markets to secure a global business coverage. For instance, seeding the supply in less appealing areas by the means of targeted marketing initiatives can generate stronger externalities that in turn can attract suppliers and further growth the network thanks to cross-side feedback loops. Second, being able to recognize differentials in CNE can be helpful when designing customer/supplier acquisition strategies. For instance, platforms' managers should be aware of the fact that seeding supply in multiple sub-market can generate different outcomes on the demand for platform-based services, such that a more efficient allocation of time and financial resources can be planned upfront the strategic decisions. Third, the recognition of discrepancies can be useful when facing particularly exogenous shocks, as reported in the following section.

[24] It is worth to notice that the model control for the share of *unsual* listings.
[25] Again, the model controls for the general price level by including the ADR in sub-market *p* at time *t*.

1.5.3. Implications for Practitioners: Shocking Suppliers Costs & consequent Effects on the Network

This paragraph provides a simulation study which, drawing on the estimated coefficients of Equations 1.12. and 1.13. (see Appendixes A1.15 and A1.16), simulates the impact of a 50% increase in the average long term rental prices on both suppliers' and visitors' entries market shares. The intuitions behind this follow-up study come from the fact that the analyses have noticed that Airbnb is primarily supply driven, such that it is of interest of managers to get to know what append if suppliers' opportunity costs (i.e., in this case the opportunity costs of the side driving the growth of the network) significantly rise. Second, to the extent that CNE are asymmetric across sub-markets, it is worth to understand how a symmetric shock on the supply side (equal, in magnitude, to all sub-markets), *differently* impact the demand side across various sub-markets. Finally, to the extent that in the moment of the finalization of the chapter[26], long term rentals are generally increasing, and rising inflation trends are increasing the cost of traveling, this kind of study can be of relevant interest to short-term-rental platforms given its timing.

The simulation spans from June 2017 to September 2019 and works as follows. In all province-time observation the value of $AvgRent_{pt}$ has been artificially increased by 50%. In line with the estimations, a direct negative effect on the entries into Airbnb supply side is expected because hosts willing to exploit their underutilized asset do face higher opportunity costs because the substitute long term rental markets provide higher (maybe more competitive) returns. Then, an indirect effect is likely to exist too. This indirect effect comes from the CNE because if increasing costs decrease the entries, lower entries will lower the stock of active properties which in turn will lower the share of visitors reserving a stay on Airbnb, which finally will have an indirect negative impact on subsequent suppliers' entries. In order to measure the impact of rising suppliers' opportunity costs the following metrics have been taken into consideration. First, to the extent of studying the direct effect of $AvgRent_{pt}$ increase, the cumulative loss of new listings and the ratio between the *simulation-derived* share of new entrants and the really observed one fixing demand at the really observed values have been computed. Second, in order to study indirect effect and cross-side effects, the former metrics have been computed by allowing demand to respond supply variations, and so on.

[Insert Table 1.7. here]

[Insert Figure 1.4. here]

Table 1.7. shows the main statistics comparing the simulated values with the real-observed ones. Figure 1.4. provides two plots, showing the evolution of supply and demand over time. Multiple findings are of interest. First, considering the supply side only, it is worth to notice the impact of CNE on the entries of suppliers. Indeed, if by fixing demand to its observed value, Table 1.7a shows a direct effect of -45.15% on the new entries, when indirect effects (i.e., cross side network externalities) are allowed to work, the drop of new hosts' entries rises up to -57.12%, depicting a total of -44,702 Airbnb lost just because of indirect effects created by CNE and not because of increasing opportunity costs. Figure

[26] Around August 2022.

1.4a shows the dynamic over time: at the beginning the direct effect is almost the only one acting on suppliers' entries, while as time goes it is possible to notice the increasing incidence of indirect effects because lower entries are discouraging demand. Second, despite the shock is primarily on the supply side, it is valuable to see in Table 1.4a that the relative impact on demand is larger rather than the impact on supply (i.e., the simulation predicts -68.50% reservations compared to -57.12% new hosts' entries). The result is not surprising: as long as Airbnb is primarily supply driven (see section 1.5.1), it is clear that supply shocks become in this setting a demand one because of indirect effects whose magnitude is rather amplified by the stronger CNE. Figure 1.4b provides the dynamic over time, showing that, while at the beginning the rising long term rental prices directly and more remarkably impact the supply side, in the long run, by the means of indirect effects working, the shock transits toward demand, hitting this side of the market more than the supply one. Third, following the sub-market characterization of CNE as in section 1.5.2., Table 1.7b shows that the impact is different with respect to different levels of supply intensity indicators. Indeed, as long as S2D externalities are stronger in local markets with higher supply intensity, the simulation shows that demand is largely shocked on average in sub-markets with higher quartiles of SI_p. This effect turns also on the supply side.

1.6. Conclusions

This study largely draws on the industrial organization literature studying either theoretically or empirically multi-sided markets, that, thanks to the recent diffusion of internet technologies, are now reshaping many industries (Guttentag, 2015; Parker & Van Alstyne, 2005; Parker et al., 2016; Cusumano et al., 2020). Among the various topics tackled by the economic literature on multi-sided markets, this analysis goes in depth toward the concept of network externalities (Katz & Shapiro, 1985; 1986; 1994) aimed at providing further knowledge either under the theoretical and empirical point of view. Starting from the flourishing literature on the empirical quantification of cross-side network externalities in multi-sided markets (ranging from Rysman, 2004, to Chu & Manchanda, 2016), this research endeavor studies the network externalities by adding a neglected point of view, the spatial one, which is a distinct feature of digital platforms like Airbnb or Uber offering localized services in multiple geographically segmented local sub-markets, characterized by their own industry structure.

Multiple findings have been derived. First, the empirical analysis has shown that Airbnb is primarily supply driven, being S2D externalities six times larger than D2S ones. Second, this study depicts that on the Airbnb platforms, producers' decisions to join the platforms are significantly shaped by the local industry structure, while the opposite is not true. In other words, S2D externalities have been noticed to be varying according to local sub-market characteristics, being a) increasing as the intensity of local supply competition increases, or b) decreasing as the touristic demand appeal rises. All these aspects have then been documented into a simulation study shocking suppliers' opportunity cost, showing that practical managerial implication can derive from this study.

The insights in this research allow multiple considerations, that are particularly relevant for both industry practitioners and the economic literature on the micro-foundation of multi-sided platforms. Indeed, in line with Kim et al. (2022), this study envisages a novel framework upon which building new theories on multi-sided platforms, confirming that, although the services are *digital*, the spatial component in some platforms matters and significantly shapes the corresponding growth trajectories. To this end, this study and the corresponding novel characterization of platforms offers a new viewpoint upon which studying the strategic management of such market structures. For instance, since the start-up of the platform is often considered one of the major concerns and source of failure in these businesses (Cusumano et al., 2020), these findings can help future platforms characterized by a spatial component (such as Airbnb or Uber) to better understand which markets deserve targeted strategic toward the supply or demand side. On the other hand, similar to the simulation provided in section 1.5.3., this study shows that when an exogenous shock symmetrically affects multiple markets in which a platform is active (such as, the Covid-19, for instance), practitioners should be aware of the fact that the outcome on platform growth is rather asymmetric, being some areas more exposed to the threat of negative loops than others.

1.6.1. Limitations and Future Development

This analysis is not exempt from limitations.

The first limitation of the paper regards the fact that all suppliers and all visitors are treated as a single group, neglecting the fact that different sub-groups of suppliers and customers can exist. In line with the increasing interest on Airbnb suppliers' professionalization (Chen et al., 2022b), a worth extension of this paper, should indeed study the utility function of Airbnb hosts by treating them as distinct subgroups. In the same way, different customer segments (i.e., high-end / low-end, inbound / outbound) should be categorized and analyzed separately.

A second limitation can be attributable to the fact that the data at disposition of the author refer to a shorter period of the platform life, neglecting the information (on the demand side) since the platform beginning. This limitation has been partially addresses by including the control variable counting the month from first Airbnb inception in the supply equation, where word-of-mouth and agglomeration effects are likely to act.

Third, following the recent contribution of Hinz et al. (2020), it can be valuable to decompose CNE in different components, as long as acquisition and churn rate can be of interests of managers. To this extent, a valuable extension of the analyses can include into the theoretical formulation the decision of service providers to leave the platform.

Finally, further extension of the prosed follow-up analyses can be of interest. In particular, studying the differential impact of seeding strategies in a simulation setting can be worthy to see how same strategies (e.g., marketing promotions artificially increasing supply or demand) have different outcomes in different sub-markets.

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Tables – Chapter 1

Table 1.1. Airbnb vs HomeAway: main performance metrics.

	AB Avg LOS / HA Avg LOS	AB Avg ADR / HA Avg ADR
Mean	0,74	0,65
Standard Dev.	0,27	0,19
Min	0,10	0,17
5th Perc.	0,41	0,38
10th Perc.	0,47	0,44
25th Perc.	0,56	0,53
Median	0,70	0,64
75th Perc.	0,87	0,76
Max	3,58	3,50

Notes:

a) AB = Airbnb, HA = HomeAway (today VRBO)
b) Avg LOS = Avg Length of Stay = Mean length of a reservation in sub-market *p* at time *t*, computed as the number of Reserved Nights in sub-market divided by the number of reservations.
c) ADR = Average Daily Rate in sub-market *p* at time *t*, computed as the ratio of total revenues to the number of reserved nights.
d) Data spans within 105 Italian provinces (sub-market *p*) and 30 months from June 2017 to December 2019 (time *t*) because of restrictions on HomeAway dataset.

Table 1.2. Descriptive Statistics.

Variable	Description	Obs	Mean	Std. dev.	Min	Max
$PR^{S,join}$	Entrant listings' share	3,779	0.002	0.003	0.000	0.034
$PR^{D,use}$	Airbnb reservations' share	3,780	0.035	0.047	0.001	0.807
δ_{tp}^{S}	Entrant suppliers' utility	3,770	-6.840	1.173	-11.089	-3.335
δ_{tp}^{D}	Visitors' utility	3,780	-3.812	1.069	-7.133	1.432
$lnD_{ptk=3}$	Log of demand	2,940	10.541	1.587	5.347	15.154
$lnDha_{ptk=3}$	Log of HA demand	2,940	8.714	1.779	2.833	13.112
$AvgRent_{pt}$	Avg long term rental prices	3,780	3.423	1.772	0.000	9.077
$PercLux_{pt}$	Share of luxury hotel beds	3,780	0.434	0.171	0.124	0.850
$lnGDPc_{pt}$	Log of per capita GDP	3,780	10.166	0.281	9.629	10.930
lnS_{pt}	Log of Airbnb stock	3,780	7.491	1.255	3.932	10.491
$lnSha_{pt}$	Log of HA stock	3,255	6.631	1.503	0.693	9.762
$SharePart_{pt}$	Share of *particular* listings	3,780	0.086	0.052	0.008	0.364
ADR_{pt}	Average daily rate	3,780	96.708	32.003	41.462	368.862
SI_{p}	Supply intensity indicator	3,780	0.537	0.229	0.048	1.000
DI_{p}	Demand intensity indicator	3,780	0.634	0.203	0.067	0.999

Notes:

a) Descriptive statistics are computed over the whole panel (all sub-market *p* and time intervals *t*).
b) HA = HomeAway
c) See sections 4.2. and 4.3. for the operationalization of the variables.

Table 1.3. Baseline Supply model estimate.

	M1	M2	M3	M4	M5	M6	M7
MFF_{pt}		0.027***	0.029***	0.028***	-0.052***	-0.065+	-0.066+
		(0.007)	(0.007)	(0.007)	(0.014)	(0.033)	(0.036)
MFF^2_{pt}		-0.000***	-0.000***	-0.000***	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$lnGDPc_{pt}$			-0.884	-0.886	-2.615***	-2.716**	-2.693***
			(0.640)	(0.615)	(0.737)	(0.804)	(0.791)
$AvgRent_{pt}$				-0.160*	-0.328***	-0.336***	-0.336***
				(0.075)	(0.092)	(0.094)	(0.094)
$PercLux_{pt}$				0.073	0.855	0.949	0.959
				(0.541)	(0.841)	(0.865)	(0.873)
$lnD_{ptk=3}$					0.673***	0.771***	0.778**
					(0.076)	(0.220)	(0.237)
$r^D_{ptk=3}$						-0.124	-0.106
						(0.266)	(0.233)
$(r^D_{ptk=3})^2$							0.363
							(1.516)
Constant	-7.130***	-8.415***	0.432	1.016	17.666*	18.605*	18.366*
	(0.020)	(0.351)	(6.450)	(6.149)	(7.344)	(8.026)	(7.879)
SE	Robust	Robust	Robust	Robust	Robust	Robust	Robust
MonthFE	yes	yes	yes	yes	yes	yes	yes
IndividualFE	yes	yes	yes	yes	yes	yes	yes
Observations	3,770	3,770	3,770	3,770	2,934	2,934	2,934
Individuals (p)	105	105	105	105	105	105	105
Overall R2	0.088	0.092	0.020	0.005	0.078	0.102	0.105
Within R2	0.439	0.443	0.443	0.443	0.428	0.428	0.428
Between R2	0.007	0.020	0.040	0.130	0.057	0.082	0.086
AIC	3,685.646	3,666.950	3,666.774	3,667.661	2,430.845	2,432.284	2,433.912
BIC	3,754.229	3,748.003	3,754.061	3,767.418	2,532.575	2,539.998	2,547.611

Notes:

a) Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.10

b) M5 uses traditional OLS, while M6 and M7 employ the two-stage approach including first stage residuals.

Table 1.4. Baseline Demand model estimate.

	M1	M2	M3	M4	M5	M6	M7
$SharePart_{pt}$			-2.469	-2.194	17.612***	22.154***	21.980***
			(5.554)	(5.465)	(2.594)	(2.404)	(2.436)
ADR_{pt}				0.006***	0.001	0.003*	0.003*
				(0.002)	(0.001)	(0.001)	(0.001)
lnS_{pt}					3.376***	4.784***	4.786***
					(0.263)	(0.210)	(0.207)
r^S_{pt}						-2.605***	-2.529***
						(0.358)	(0.444)
$(r^S_{pt})^2$							0.561
							(0.983)
Constant	-3.802***	-3.733***	-3.521***	-4.211***	-30.300***	-41.659***	-41.653***
	(0.027)	(0.099)	(0.483)	(0.538)	(2.082)	(1.701)	(1.686)
SE	Robust	Robust	Robust	Robust	Robust	Robust	Robust
NUTS2*QuarterFE	no	yes	yes	yes	yes	yes	yes
MonthFE	yes	yes	yes	yes	yes	yes	yes
IndividualFE	yes	yes	yes	yes	yes	yes	yes
Observations	3,780	3,780	3,780	3,780	3,780	3,255	3,255
Individuals (p)	105	105	105	105	105	105	105
Overall R2	0.062	0.058	0.010	0.069	0.292	0.276	0.276
Within R2	0.147	0.170	0.171	0.185	0.602	0.620	0.620
Between R2	.	0.001	0.106	0.006	0.404	0.399	0.399
AIC	7,403.788	7,389.138	7,388.382	7,322.763	4,621.561	3,694.635	3,695.305
BIC	7,472.400	7,738.436	7,743.918	7,684.537	4,989.572	4,059.912	4,066.670

Notes:

a) Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.10

b) M5 uses traditional OLS, while M6 and M7 employ the two-stage approach including first stage residuals.

Table 1.5. Baseline CNE estimate.

	D2S Elasticity	S2D Elasticity
at Mean	0.769***	4.615***
	(0.219)	(0.202)
at 1st P.	0.771***	4.776***
	(0.220)	(0.210)
at 25th P.	0.770***	4.734***
	(0.220)	(0.208)
at Median	0.770***	4.678***
	(0.220)	(0.205)
at 75th P.	0.769***	4.576***
	(0.219)	(0.201)
at 99th P.	0.759***	3.774***
	(0.216)	(0.166)

Notes:

a) Elasticities computed as reported in section 4.3.4.

b) Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.10.

c) D2S elasticities are computed at different values of $PR^{S,join}$ (Airbnb share of entrant listings), while S2D elasticities are computed at different values of $PR^{D,use}$.

Table 1.6. Sub-market varying CNE.

	D2S CNE	S2D CNE		D2S CNE	S2D CNE
SI_p = 0%	0.788***	4.790***	DI_p = 0%	0.788***	4.790***
	(0.228)	(0.406)		(0.228)	(0.406)
SI_p = 10%	0.793***	5.073***	DI_p = 10%	0.779***	4.549***
	(0.232)	(0.379)		(0.223)	(0.381)
SI_p = 20%	0.798***	5.356***	DI_p = 20%	0.769***	4.310***
	(0.236)	(0.361)		(0.220)	(0.364)
SI_p = 30%	0.802***	5.640***	DI_p = 30%	0.760***	4.070***
	(0.242)	(0.352)		(0.216)	(0.355)
SI_p = 40%	0.807***	5.923***	DI_p = 40%	0.750***	3.830***
	(0.247)	(0.354)		(0.213)	(0.355)
SI_p = 50%	0.812***	6.207***	DI_p = 50%	0.740***	3.590***
	(0.252)	(0.366)		(0.210)	(0.363)
SI_p = 60%	0.816***	6.490***	DI_p = 60%	0.731***	3.350***
	(0.258)	(0.387)		(0.208)	(0.380)
SI_p = 70%	0.821***	6.774***	DI_p = 70%	0.721***	3.111***
	(0.264)	(0.417)		(0.206)	(0.405)
SI_p = 80%	0.826***	7.057***	DI_p = 80%	0.712***	2.870***
	(0.270)	(0.453)		(0.205)	(0.436)
SI_p = 90%	0.830***	7.341***	DI_p = 90%	0.702***	2.630***
	(0.276)	(0.494)		(0.204)	(0.472)
SI_p = 100%	0.835***	7.624***	DI_p = 100%	0.692***	2.390***
	(0.283)	(0.539)		(0.204)	(0.511)

Notes:

a) Elasticities computed as reported in section 4.3.4.

b) Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.10 test the elasticity at specific values of SI_p or DI_p to be significantly different from 0.

c) Elasticities are computed after the estimation of Eq. 12 and 13, employing a linear control function. Results with standard OLS and quadratic control function are available upon request to the authors.

d) The full regression outputs are available in Appendix 15 (for D2S elasticities) and 16 (for S2D elasticities).

Table 1.7. Simulation results.

Table 1.7a. Italian level simulation output.

	Real (Observed)	Direct Effect [DE]	Direct & Indirect Effect [DIE]	Indirect Effect [DIE - DE]
Total n^S	373,308	204,795	160,093	-44,702
Δ Effect-Real		-45.14%	-57.12%	-11.98%
Mean $Pr^{S,join}$	0.21%	0.11%	0.09%	-0.02%
Δ Effect-Real		-47.69%	-59.28%	-11.59%
Total n^D	23,582,877	n.a.	7,427,855	n.a.
Δ Effect-Real		n.a.	-68.50%	n.a.
Mean $Pr^{D,use}$	3.27%	n.a.	1.01%	n.a.
Δ Effect-Real		n.a.	-68.96%	n.a.

Notes:

a) Simulation output is based on the estimation results of Eq. 12 and 13 (Appendixes 15 and 16), and are obtained by artificially increasing $AvgRent_{pt}$ by 50%.

b) Real (Observed) = values observed by AirDNA in real life; DE = Simulation results with demand levels fixed to real (observed values); DIE = Simulation results with demand levels adapting to supply variations.

c) Total n^S = total new Airbnb in Italy; Mean $Pr^{S,join}$ = average entrant suppliers market share over the Italian country; Total n^D = total reservations on Airbnb in Italy; Mean $Pr^{D,use}$ average Airbnb market share of reservations over the Italian country.

Table 1.7b. Simulation output by quartiles of SI_p.

Quartile SI_p	$\mathbf{Mean\ Pr_{pt}^{S,join,DIE}}$ / $\mathbf{Mean\ Pr_{pt}^{S,join,OBS}}$	$\mathbf{Mean\ Pr_{pt}^{D,use,DIE}}$ / $\mathbf{Mean\ Pr_{pt}^{D,use,OBS}}$
1	0,478	0,366
2	0,506	0,342
3	0,459	0,316
4	0,324	0,237

Notes:

a) Simulation output is based on the estimation results of Eq. 12 and 13 (Appendixes 15 and 16), and are obtained by artificially increasing $AvgRent_{pt}$ by 50%.

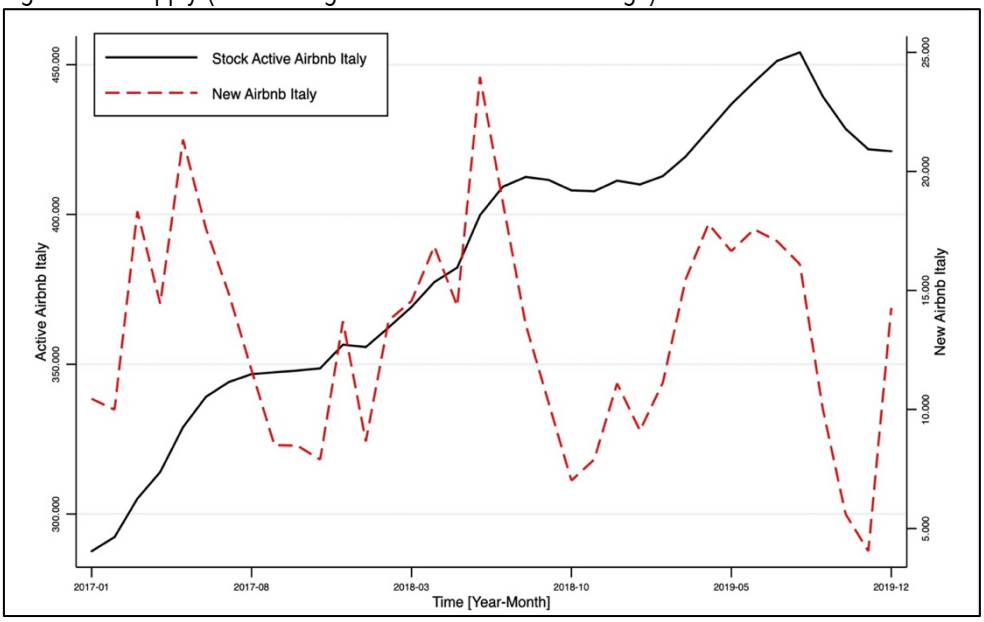
b) DIE = Simulation of suppliers' entries or visitors' reservations with direct and indirect effects; OBS = observed values in reality.

c) Mean $Pr^{S,join}$ = average entrant suppliers market share over the Italian country; $Pr^{D,use}$ average Airbnb market share of reservations over the Italian country.

Figures – Chapter 1

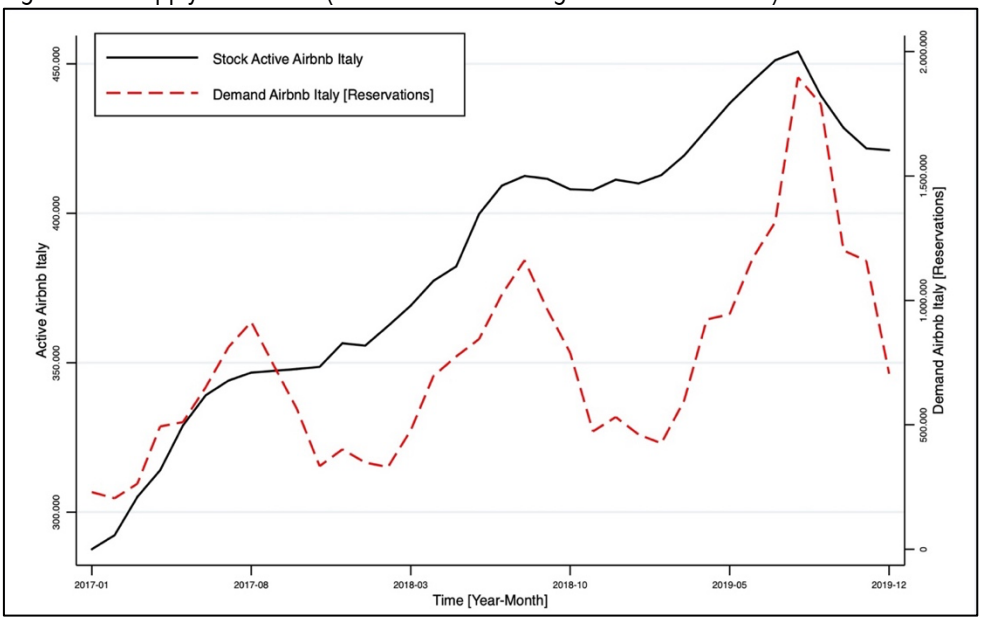
Figure 1.1. Supply and Demand evolution at the Italian level.

Fig. 1.1a – Supply (New Listings and Stock of Active Listings)



Notes:
a) Source: Author's calculation on AirDNA data.
b) The data are aggregated at the country (Italian) level by summing data per each panel.

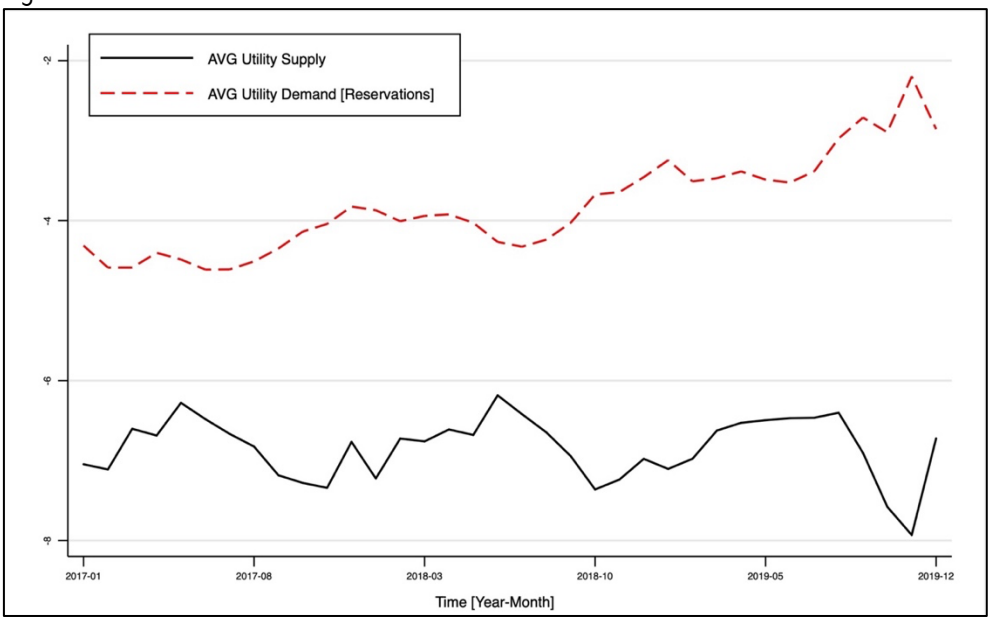
Fig. 1.1b – Supply & Demand (Stock of Active Listings and Reservations)



Notes:
a) Source: Author's calculation on AirDNA data.
b) The data are aggregated at the country (Italian) level.

Figure 1.2. Supply and Demand Utility.

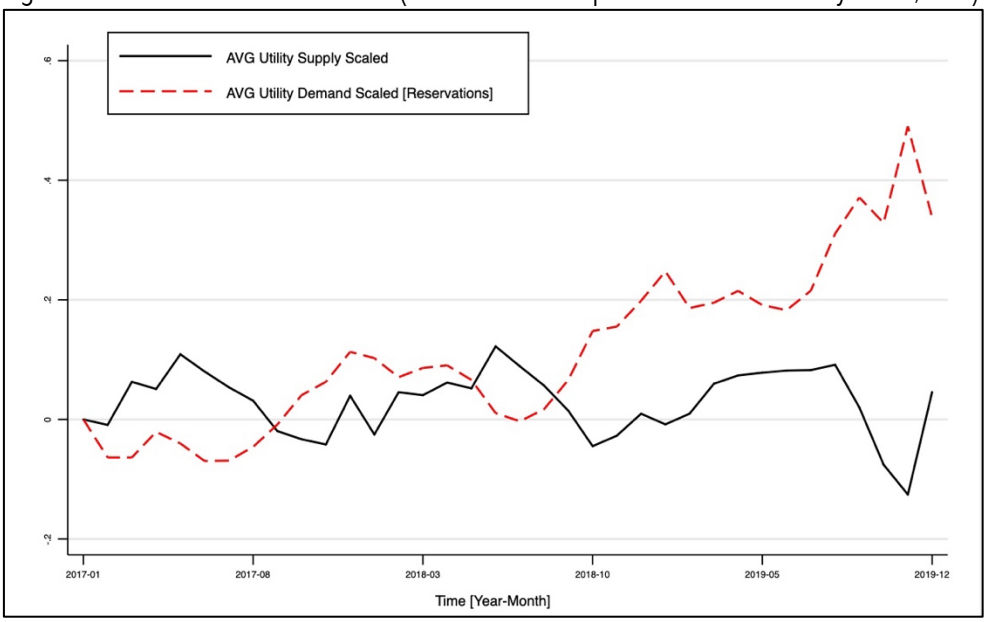
Fig. 1.2a – Utilities in absolute values



Notes:

a) The data are aggregated at the country (Italian) level taking the mean value between each sub-market *p*.

Fig. 1.2b – Utilities in relative values (scaled on the respective value at January 2017, t=1)



Notes:

a) The data are aggregated at the country (Italian) level taking the mean value between each sub-market *p*.

Figure 1.3. Sub-market varying CNE plot.

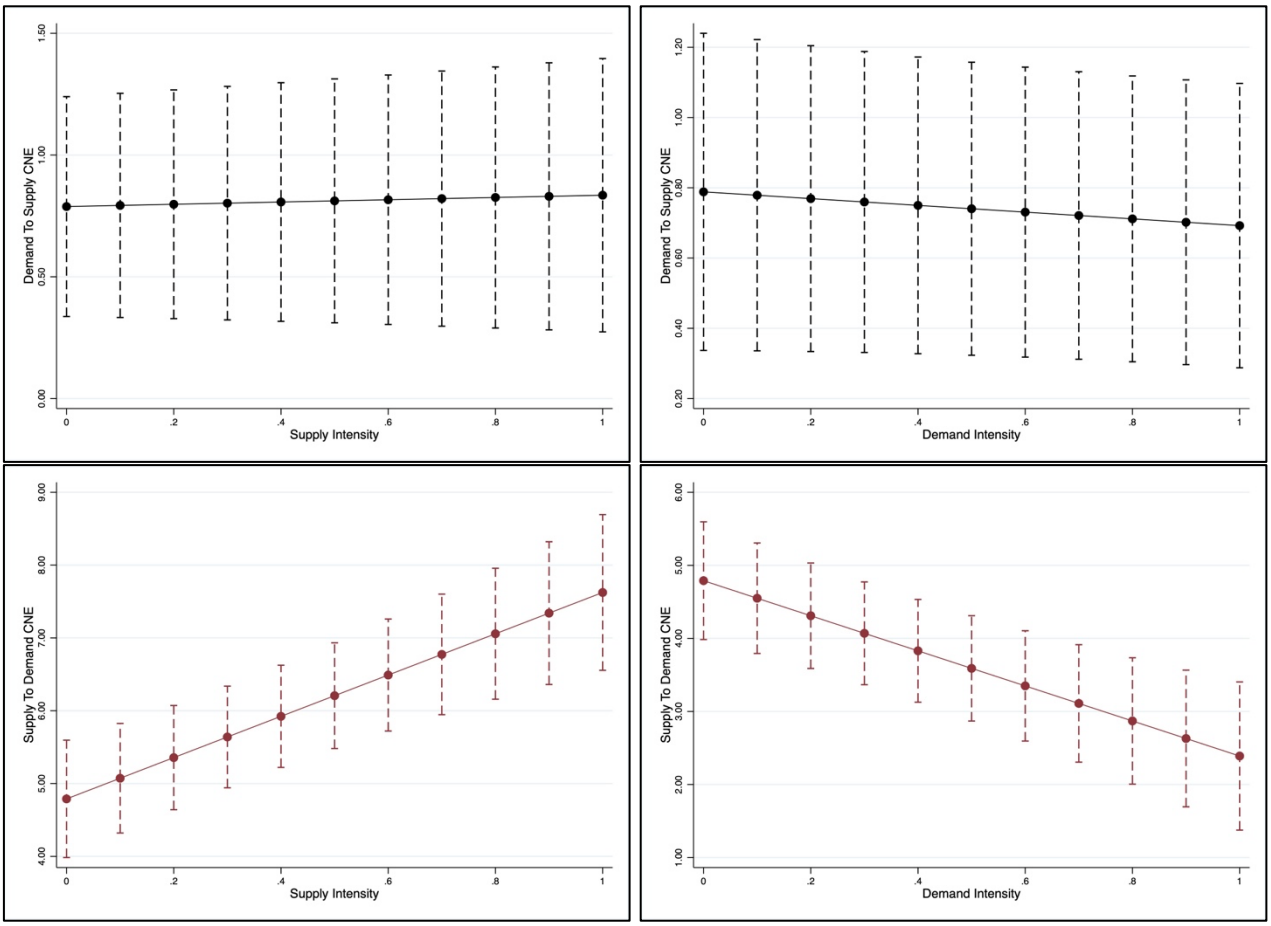
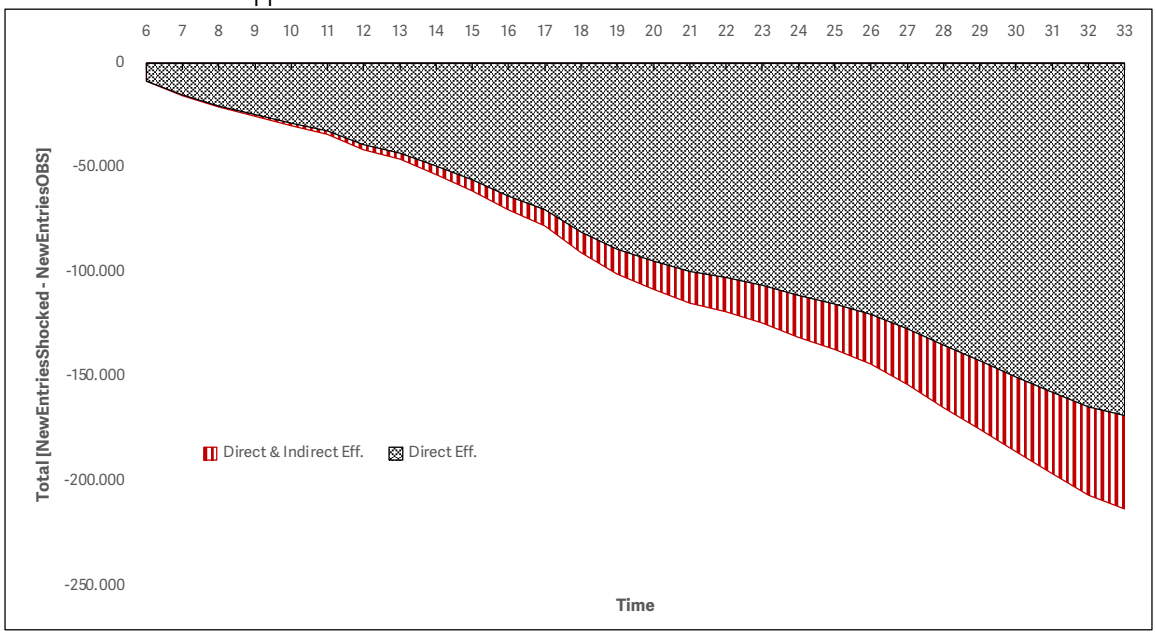


Figure 1.4. Simulation graphical outputs.

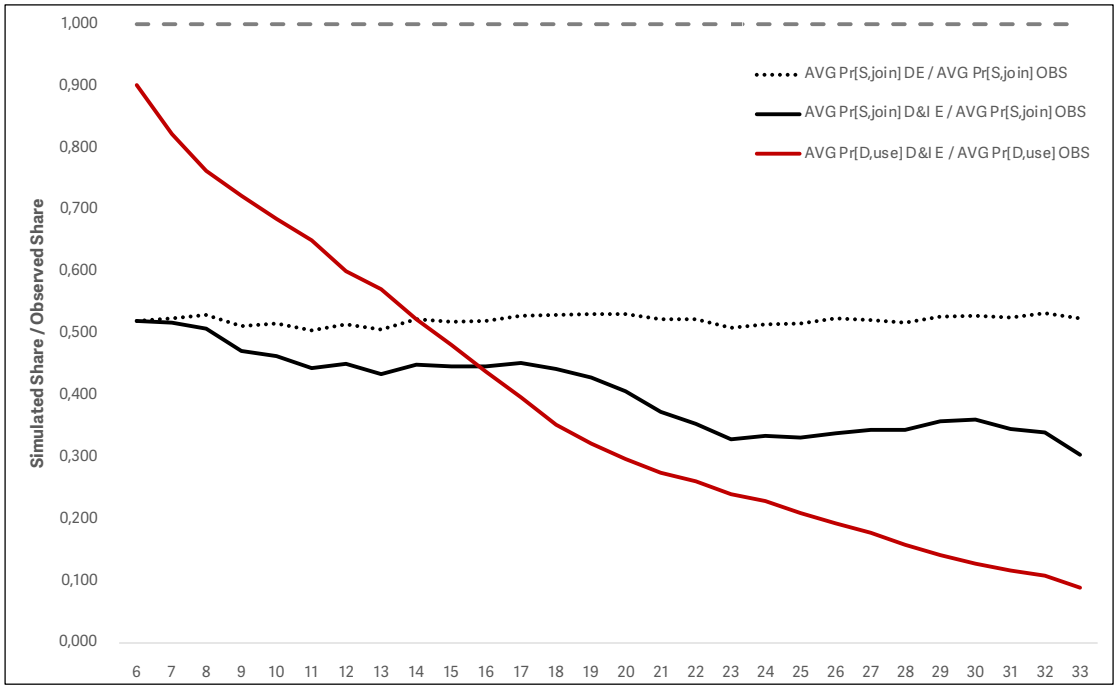
Figure 1.4a. Total lost new suppliers' entries.



Notes:

a) Direct Eff. = New Entries in Simulation with demand *fixed* to observed values – New Entries observed
b) Direct & Indirect Eff. = New Entries in Simulation with demand *responding to supply variations* – New Entries observed
c) Data are summed over the whole Italian territory; T = 6 = June 2017; T = 33 = September 2019.

Figure 1.4b. Simulated Shares to Observed Shares.



Notes:

a) Red line = Mean $Pr^{D,use}$ simulated / $Pr^{D,use}$ observed (with indirect effect)
b) Black line = Mean $Pr^{S,join}$ simulated / $Pr^{S,join}$ observed (with direct and indirect effect)
c) Black dotted line = Mean $Pr^{S,join}$ simulated / $Pr^{S,join}$ observed (with direct effect)

CHAPTER 2

Opportunities do not arise in an "industry vacuum": platforms as external enablers, local market contexts and different forms of entrepreneurship

Abstract

Successful sharing economy platforms are often digital external enablers of entrepreneurship. We claim that their potential in terms of entrepreneurial opportunities is not always the same across different 'market contexts'. This study investigates how the characteristics of a given local market influence entrepreneurship enacted by a platform in that specific geographically-bounded area. Specifically, we focus on the hospitality industry and the Airbnb platform where markets are spatially-segmented and entrepreneurs can endogenously decide their 'scale of operations', i.e., we observe the presence of small-scale entrepreneurs managing one or a few dwellings and relatively large entrepreneurs managing multiple listings. Thanks to a NUTS3 level dataset and the use of GMM methodologies, we highlight how small and large entrepreneurs are equally driven by the perceived demand size and labor market conditions, but the two typologies of entrepreneurs show different patterns when seizing opportunities in relation to competition structure, the quality of demand and opportunity costs. In particular, the entry of small entrepreneurs appears rather insensitive to the local supply-side structure, e.g., spatial concentration, while large entrepreneurs do care about it. Interestingly, the decision of entrepreneurs to scale from a small to a large-scale is determined by the same sound economic reasoning which drives entry with a large-scale of operations in the first place.

Keywords

Digital Platforms; Entrepreneurship; Airbnb; Hybrid Entrepreneurs

Credits & Acknowledgments

This chapter is extrapolated from a paper jointly written with Prof. Luigi Buzzacchi (Politecnico di Torino) and Prof. Luca Grilli (Politecnico di Milano).

The author(s) thanks to FULL – The Future Urban Legacy Lab for its financial support. I am grateful to participants in the Research Seminar Series at Audencia Business School (Nates, France) and Modul University Vienna (Austria) for their valuable suggestions and the attendees of the XXXII AiIG Annual Scientific Meeting in Naples. Finally, I thank Marco Formentini and Elisa Ughetto for their insights on an earlier draft.

2.1. Introduction

Starting from the limitations of the previous chapter, this chapter studies the entry dynamics within the Airbnb supply side, questioning and estimating the local determinants of the decisions to entry of the different types of entrepreneurs involved in Airbnb (Dogru et al., 2020a). It is widely known, in fact, that departing from the traditional sharing economy framework (Frenken & Schor, 2017), Airbnb is hosting on the supply side a fast-growing share of professional hosts, who approach the platform with a different scale of operations (Dogru et al., 2020a). In line with this evidence, other than studying only the entry process of entrepreneurs on Airbnb supply side, this chapter investigates whether differentials in the entry processes of small-scale (defined as those hosts entering the market with a limited number of listings, i.e., representing the *typical* peer active in the traditional sharing economy framework, Franken & Schor, 2017) and large-scale entrepreneurs (professional hosts entering and working on Airbnb with multiple listings simultaneously, thus running a large scale business) exist. In doing this, this chapter takes the perspective of the external enabler introduced by Davidsson et al. (2020), questioning and arguing that Airbnb can act as enabler for prospective entrepreneurs, by enabling different approaches to entrepreneurship (Folta et al., 2020) and unveiling novel opportunities (Shane & Venkataraman, 2000; Kirzner, 1973; Schumpeter, 1912/34).

In this vein, this chapter presents a study which provides novel insights to the entrepreneurship literature to the extent that the theoretical framework of the external enabler (Davidsson et al., 2020) has been empirically tested on a relevant example, Airbnb. In doing this, this chapter contends and expand the current knowledge (and the previous chapter, Chapter 1) in multiple ways: first, it shows the extent to which the seizing of entrepreneurial opportunities potentially available because of a digital external enabler is driven by locally bounded market conditions, focusing on the role of entry costs and same side externalities (which have been marginally analyzed in Chapter 1), and, more importantly, it investigates whether there are significant differences in these local market drivers for different types of entrepreneurs (small-scale and large-scale, i.e., professional, ones), highlighting the tendency for a *gradual* approach to the entrepreneurial act that is made possible by the distinct feature of the digital platform.

The rest of the chapter is organized as follows. Section 2.2. briefly revises the major contributions to the literature of entrepreneurship, external enablers, and the role of local conditions in shaping entrepreneurial act, providing the basis for the theoretical formulations of the hypotheses. Section 2.3. shows the data, the variables employed and the empirical methodologies. Section 2.5. illustrates the results and a wide set of robustness checks, while Section 2.6. provides a discussion of the results and a sub-section on the directions for future improvements of the research.

2.2. Related Literature, Research Positioning and Theoretical Background

To the extent that this research spans within multiple strands of literature, this section is articulated as follows: first it introduces the general framework, describing the concepts of business opportunities and introducing the framework of the external enabler (Davidsson, 2015), second it explores the determinant of entrepreneurial entry, also looking at local

market conditions such as demand, opportunity costs and concentration (thus re-calling traditional IO literature, Carree & Thurik, 1999) and consequently deriving the hypotheses for the following empirical application.

2.2.1. Entrepreneurial/Business Opportunities, External Enablers & Research Positioning

The seizing of business opportunities represents the heart of entrepreneurship (Shane & Venkataraman, 2000, p. 218); and accordingly, the literature has long debated (Kirzner, 1973, Schumpeter, 1911/34,) and still debates today (McBride and Wuebker, 2022; Davidsson, 2022) on the nature of entrepreneurial opportunities, i.e., what they are (Hansen et al., 2011; 2016; see Table 2 in Davidsson, 2016), whether they are discovered (e.g. Eckhardt and Shane, 2013) or endogenously created (e.g. Alvarez et al., 2013). Some scholars challenge the usefulness of constructing this latter and other dichotomies (see McMullen et al., 2007; Davidsson 2021) and also question the scientific value of the opportunity construct itself and call for its reconceptualization (e.g. Davidsson, 2015; Davidsson, 2021; Foss & Klein, 2020); while others have affirmed (e.g. Shane, 2001, 2003; Ardichvili et al., 2003; Baron & Ensley, 2006), and still affirm today (Nambisan et al., 2018; Suddaby et al., 2015), its conceptual validity. Clearly, these differences reflect the importance of studying what spurs individuals to embark on the entrepreneurial adventure, given the relevant economics and policy implications that may descend from this type of analysis.

In this domain, the concept of external enablers (Davidsson, 2015; Davidsson et al., 2020; Kimjeon & Davidsson, 2022) has recently been put forward capturing the influence on entrepreneurial action "exerted by external conditions such as new technologies; regulatory or demographic shifts; and changes to the sociocultural, economic, political, or natural environments" (Davidsson et al., 2020, p. 311). The idea is that 'external raw material' (Davidsson et al., 2020, p. 314) creates the conditions for which some individuals (and not others) seize a business opportunity which would not have been possible without 'the enabler'. The enabling potential of these external sparklers can clearly be strongly contextual (Johns, 2006; Welter, 2011; Zahra et al., 2014), where the extent to which (some) "entrepreneurial agents strategically or fortuitously make use of the potential provided by external enablers, and how enablers and their effects interact with contextual factors" is still an important question which Davidsson et al. (2020, p. 315) explicitly leave to future research.

Grounding on this research gap, and similarly to other recent examples in literature on digital technologies (Nambisan et al., 2018; von Briel et al., 2018; Nambisan & Baron, 2021; Chalmers et al., 2021), this study envisages a two-sided sharing economy platform (i.e., a digital platform exhibiting indirect network externalities, see Stallkamp & Schotter, 2021) as an external enabler for entrepreneurship. Consistently, the research question tackled by this research is:

RQ: How do individual decisions to pursue entrepreneurial opportunities, and the ways they eventually do it, are shaped by the specific local industry conditions of the markets in which the digital platform operates? In other terms, how does the digital external enabler interact with a local market context in shaping entrepreneurial action?

In fact, entrepreneurial opportunities are always subject to the proof of markets, and these markets may often have a local contextual dimension (Welter, 2011; Baker & Welter, 2018). It is therefore legitimate to expect that specific locally-bounded market conditions may incentivize or depress entrepreneurial dynamics which are enacted by the digital platform.

Rather surprisingly, how typical local characteristics of a market – barriers/costs to entry, demand and its characteristics, number, and nature of competitors – influence the decision to become an entrepreneur in that market have been rather insufficiently researched so far, despite the clear interest and policy relevance that this domain exhibits (see Fischer & Nijkamp, 2009; Davidsson et al., 2020). In fact, entrepreneurship does not happen in a vacuum (Lerner, 2009; Stam & Welter, 2020) but does happen in markets, and from markets it is clearly shaped. Thus, we extend the 'external enablement' framework towards the 'contextual entrepreneurship' view (Welter, 2011; Baker & Welter, 2018), by adopting the 'market' lens, i.e., investigating how specific spatially-bounded market conditions may influence the extent to which potential business opportunities created by a digital platform enabler are actually exploited by individuals, who in becoming entrepreneurs, may choose different levels of investment and commitment, i.e. a different scale of operations.

For this aim, this study focuses on the entrepreneurial activity in a specific industry – tourism – that has experienced the advent of the sharing economy platform Airbnb. We take advantage of the private commercial dataset which reports all Airbnb hosts recorded in Italy between 2017 and 2019. These data have been categorized into different types of Airbnb-platform suppliers, i.e., small-scale entrepreneurs managing one or a few dwellings and relatively large entrepreneurs managing multiple listings and linked to geographically-bounded characteristics of the local market (at NUTS3-level) on which these different types of entrepreneurs operate.

The potentially gradual and modular way of seizing entrepreneurial opportunities through this digital platform enabler (Li & Srinivasan, 2019; Gerwe et al., 2022) poses two additional and strictly related reflections. On one side, it challenges the idea, rooted in the industrial organization stream (Carree & Thurik, 1999; Haynes & Thompson, 2013), of a fixed carrying capacity of an industry that uniformly governs the flow of firms' entry in any given market. On the other, digital platform-based businesses may in principle allow prospective entrepreneurs to adopt a 'test the waters' approach: they may learn about their ongoing entrepreneurial acts beyond pre-entry learning only (Bennett & Chatterji, 2019). The relatively low level of entry and exit costs – and also the possibility of a gradual approach – could incentivize prospective entrepreneurs to enter the arena, test how the market responds to their new offer, then selectively choose whether to continue by upscaling their (personal and financial) investment or maintain a limited commitment and eventually leave the market (e.g. Jovanovic, 1982). Hybrid forms of entrepreneurship (Wennberg, et al. 2006; Folta et al., 2010; Raffiee & Feng, 2014; Gänser-Stickler et al., 2022) are more common than usually thought and are often considered a necessary steppingstone before part-time entrepreneurs opt to migrate towards a full-time involvement in their business. In this respect, the extent to which local market factors may influence the 'scaling up' of the entrepreneurial endeavor through an external enabler has not been investigated yet.

2.2.2. Entrepreneurship through Digital Platform Enabler: The Role of Local Conditions

2.2.2.1. General overview on the literature about determinants of entrepreneurial entry

Determinants of entrepreneurial acts have been largely investigated by the literature in entrepreneurship. Although, it is not the intention of the current study to provide an exhaustive review of all these contributions, it is possible to form a

distinction between the following three types of approach, along with the unit of analysis adopted (for an identical classification see Dvouletý, 2018; see also Davidsson & Wiklund, 2001 for the seminal logic).

On one hand, and quite naturally, some of this literature has focused its attention on the micro-level – the individual (or team) level. Since entrepreneurial acts are pursued by individuals or teams of individuals, many studies have concentrated their enquiries on the individual characteristics and psychological traits (Chell et al., 1991; Lee et al., 2004; McGrath et al., 1992) which, among others, may lead individuals to identify entrepreneurial opportunities and (eventually) actively pursue them (de Jong & Marsili, 2015; Shane, 2000).

On the other hand, there is an equally relevant body of research that has mostly focused on the macro-level of analysis – the country level (e.g. Arin et al., 2015; Bosma et al., 2018; Carbonara et al., 2016; Chowdhury et al., 2019; Freytag & Thurik, 2007; Valdez & Richardson, 2013). These studies typically investigate the role that coarse-grained characteristics in terms of geographical, economic and institutional factors play at macro-level (e.g. financial stability, public sector size, inflation rates, education, cultural aspects) in fuelling total entrepreneurial activity and national entrepreneurship rates.

A third group, which tackled a "meso" level of investigation has been, until recently, less frequently explored (for an identical view see Fischer & Nijkamp, 2009; Sternberg, 2009; see also early statistics provided in Davidsson & Wiklund, 2001) but particularly enlivened in the last period by the entrepreneurial ecosystem concept (Stam, 2015; Stam & van de Ven, 2021), aiming at analyzing the local drivers behind the creation of innovative start-ups and productive entrepreneurship (e.g. Antonietti & Gambarotto, 2020; Fritsch & Aamoucke, 2013; Fritsch & Wyrwich, 2018; Colombelli, 2016). This "meso-level" is however silent on the way specific characteristics of a given local market may have an impact on the entrepreneurship rate in that specific geographically-bounded market rather than at general level, and it remains clearly to be explored the extent to which the enablement potential of a sharing economy platform may depend on the specific market context where prospective sellers would eventually operate.

From this "market contextual" perspective (Welter, 2011), the main explanatory variables this study is interested in are associated with different local market conditions, and in particular they are: i) the perceived demand by potential prospective entrepreneurs and the level of entry and operating costs; ii) the toughness of competition, i.e. the local level of spatial concentration.

2.2.2.2. Demand and Opportunity Costs

The structural market variables that might exert an impact on the decision to enter are first determined by beliefs and convictions about expected demand and costs. The higher the demand (or the growth rate of demand), the more it is likely to expect room for new firms in the sector (Ateljevic & Page, 2009). Consequently, during periods of increasing demand, entrants are attracted by profit opportunities, also considering that the business model (on Airbnb platform) is such that most of the incumbents are not normally in a condition to expand their capacity. Moreover, potential entrants expect to obtain larger profit margins when their costs are lower. Entry studies (e.g. Geroski, 1995) normally control

these effects, with demand and costs that should exert a positive and a negative impact, respectively, on entry dynamics. However, both demand and cost variables require further discussion in our framework.

If, quite naturally, a higher demand in a local market is expected to make (whatever type of) entrepreneurs more willing to enter that market, the prevalence of specific demand segments (due to the heterogeneity of platform users on the demand side) can create more room for a specific typology of new entrant rather than another. Moreover, (potential) entrepreneurs may have a differentiated ability to identify and respond to the changing environment, and normally they do not have the instruments for estimating the actual (and future) demand on the market, rather they perceive some measure of the 'market climate', i.e., they receive signals and clues about the level of prospective entrepreneurial opportunities at the local level. However, compared to the following determinants of entry (namely, entry costs) it is likely that, even if large-scale entrepreneurs, conducting the business in a more professional manner (Dogru et al., 2020a), may have access to a more precise information about demand signals, small-scale ones can easily detect periods of positive or negative market climate thanks to multiple effects (e.g., among the others, local market knowledge, information effects between peers and/or information pushed by the platform to the suppliers). To this end, it is likely that perceived demand symmetrically (and positively) affects the entry of both kinds of entrepreneurs.

HP1: Higher perceived demand at local market level positively affects the entry of new entrepreneurs.

As for the costs (entry costs, in particular), they are endogenously determined by the scale of operations. If the opportunity costs of entry are low, entry will be more likely, but this is particularly true for small entrepreneurs, as they would not need to incur significant sunk costs (which large-scale entry is likely to entail, see below). For most small entry scales, few physical assets and some time for managing the business could be sufficient to start (Garcia-López et al., 2020). When the opportunity cost of time is low (cf. Dogru et al., 2020b; Fang et al., 2016) and the assets needed for entry would otherwise remain undervalued or underutilised, small-scale entry entrepreneurs will have 'nothing to lose' in 'trying' (Gänser-Stickler et al., 2022), i.e., small-scale entry should be particularly stimulated in local markets characterised by a relatively low opportunity cost in the use of inputs.[27] This 'testing the waters' attitude that is often possible through sharing economy platforms, could also lead to a phenomenon of 'oversupply', i.e., an incentive to enter even if profitability is below the normal profit rates.

HP2a: Lower opportunity costs to enter at local market level have a more positive effect on the entry of small entrepreneurs than large entrepreneurs.

However, services and facilities designed for high-range consumers, who are more (less) sensitive to quality (prices), should require significantly higher amounts of investment (e.g., marketing, advertising, and back-office activities) and a higher standard of services which require a certain degree of competence and preparation. Moreover, some portions of

[27] For example in case of Airbnb, available rooms/apartments cannot be easily placed on the rental market if the supply of empty dwellings is high.

these investments could well exhibit non-fully re-deployable characteristics. Thus, both the size and the nature of the investments likely required make us hypothesize that large-scale entrepreneurs will be particularly sensitive to the presence of high-range prospective customers, who may ensure higher revenues (by the means of a higher willingness to pay for the supplied services) on the one side, therefore justifying the undertaking of these large-scale investments, and being in line with the larger skill set and domain expertise of such entrepreneurs when compared to small-scale entrepreneurs on the other.[28]

HP2b: The high-range specialization of an industry has a more positive effect on the entry of large entrepreneurs than the entry of small entrepreneurs.

2.2.2.3. The Role of Industry Concentration

Traditional Industrial Organization (IO) models suggest that profitability, and consequently entry rates, are expected to be higher, all else being equal, where the competition is mild (see Cabral, 2017 among others). However, spatial concentration of the local market may affect entrepreneurs' willingness to enter in three different ways.

A. Information effects. A necessary (albeit not sufficient) condition for seizing entrepreneurial opportunities is the availability of related information that triggers individuals' interest in engaging in the creation of a new venture (Ardichvili et al., 2003). Such information can also be spread through unintended word-of-mouth communication, simple observation, and imitation or social influence (Kacperczyk, 2013). Bunten et al. (2015) and the literature they cite stresses the crucial role of entrepreneurial marketplace information for regional endogenous growth, in particular as a determinant of entry and exit rates. In this respect, we argue that a higher density of sellers through the platform in the local market may increase the probability that potential entrants obtain a bulk of information that is sufficient to convince them to enter the market. Conceivably, the effect of concentration on information tends to saturate when a sufficient level of concentration is reached.

B. Cluster effects. Economic literature suggests that service providers – when the product is differentiated and prices are dispersed – might want to "locate" near other competitors to enjoy proximity benefits[29]. In other words, sellers might

[28] Consistent with this, the literature clearly shows that the competition of Airbnb hosts with traditional hotel supply can be associated with very different strategies (Chang & Sokol, 2020). There is no clear evidence to indicate whether the competition of Airbnb is more effective in the segment of low- or high-category hotels. Zervas et al. (2017) analyse the case of Texas and provide evidence of a negative effect on revenues in the hotel industry caused by competition from Airbnb provision; however, this effect is largely concentrated in the low category hotels. Farronato & Fradkin (2022) estimate, using data from 50 big American cities, that the entry of Airbnb entrepreneurs has a significant influence on hotel prices (more than on the occupancy rate), especially when demand is more elastic and the hotel supply is capacity-constrained, which happens more consistently in the segment of higher category hotels. Dogru et al. (2019) demonstrate that in ten major U.S. hotel markets the (negative) impact of Airbnb on hotel performance is significant across various hotel class segments. These blurred findings are likely to be associated with the differentiated Airbnb supply and with the co-existence of various types of entrepreneurs.

[29] The early literature on product variety, (free) entry and social welfare (e.g. Spence, 1976, and then Mankiw & Whinston, 1986) is one-side modelled and the demand of consumers is usually assumed to be fixed. In such literature, the decision to enter or not depends on the trade-off between competition effects (more firms, lower profits) and the preference for variety of consumers (a cluster of firms jointly offering greater variety could increase consumers' willingness to pay). Recent literature on platforms (or two-sided markets) introduces indirect network effects: consumer preferences for variety also determine an increase in total demand associated with entries on the supply side (see, e.g. Hagiu, 2009).

prefer locating near other sellers because together they could be more attractive for consumers who might want to compare services and prices before making any purchase[30]. In this sense, a critical mass of physically close competitors might more easily convince individuals on the demand side to opt for consuming rather than a situation where options in terms of sellers' choice are numerically limited (Xie et al., 2020), consequently allowing incumbents to set higher prices (McCann & Vroom, 2010)[31].

C. Competition effects. While the advantage of proximity to other sellers (point B) tends to incentivize spatially correlated entries, competition caused by concentration could discourage entrepreneurial acts (see again Baum & Haveman, 1997; Economides, 1986). Competition effects determine that the entry of new firms dilutes the profits of the incumbents. However, classic oligopolistic models suggest that profits will not necessarily be driven to zero by entry if barriers to entry (in particular space and scale effects) are at work (Eaton & Lipsey, 1978). In any case, when a suitable threshold level of concentration (i.e. profits) is reached, new entries are normally discouraged. Notice that interpreting market signals on the supply side can be costly (see, for the tourism industry, Lerner & Haber, 2001); moreover, this negative competition effect is subjectively perceived as more deterring for those individuals bearing higher entry costs. For both reasons, large-scale entrepreneurs are more likely to be discouraged by a high level of competition.

The equilibrium between the pros and cons of concentration must be considered as one of the main drivers of the entry/exit process. All else being equal, for lower levels of concentration competition forces would probably have negligible effects, while new entries can further fuel new entrepreneurial phenomena for information/agglomeration reasons. Conversely, above a certain threshold of concentration, it is legitimate to expect competition effects to prevail and entry to be discouraged. Thus, the combination of these forces A, B, and C would lead to an expected bell-shaped curve describing the relationship between concentration and entry. Predictions about the effects of concentration in (different) markets are then based on the notion of an equilibrium rate of business ownership (Audretsch & Fritsch, 2002; Carree & Thurik, 1999; Hartog et al., 2010), a concept sometimes referred to as the 'market's carrying capacity' in organization ecology literature (Hannan & Freeman, 1977). If 'excessive entry' is observed, this leads to market overcrowding. The empirical evidence on the role of carrying capacity in deterring entry is limited (see in particular the analysis by Carree & Thurik, 1999, for the Dutch retailing sector), and completely absent in case of entrepreneurial entries via the digital external enablement of a sharing economy platform. In this latter case, we advance the idea that an 'excessive entry' cannot be excluded, and it is indeed likely, because entry costs – especially for small entrepreneurs – are low and non-sunk, as discussed in the previous section.

Thus, it is likely that the entry discipline governed by the concentration-related effects depicted in points A, B and C, which altogether connote firm entry based on solid economic reasoning, to be relevant only for large rather than small entrepreneurs using the platform. It is expected this to be true for multiple reasons: a) first, as argued in the previous

[30] In the Airbnb case, it is documented the preference of prospective consumers to see a sufficiently differentiated offer in the area where they plan to stay (Baum & Haveman, 1997).
[31] For a similar point of view in the hotel industry see Chung & Kalnins (2001).

section, low and non-sunk entry costs make the entry attractive to small-scale entrepreneurs, leading to excessive entry of small-scale entrepreneurs regardless the actual thickness of supply competition which hurts profits, and b) to the extent that the interpretation of concentration signals requires solid economic reasoning and a corresponding economic skill set able to identify market overcrowding, large scale entrepreneurs may leverage their decision on these signals also. Thus, in the relationship between concentration and entry, we hypothesize that entry is governed by a bell-shaped relation for large platform-based entrepreneurs only, not small ones. Consistetly, It is possible to formulate the following hypotheses:

HP3a: Industry concentration at local market level only affects the entry of large entrepreneurs, not the one of small entrepreneurs.

HP3b: The relationship between concentration and entry of large entrepreneurs is bell-shaped.

2.2.2.4. Staged Large Entry

As said above, acquiring knowledge about the factors affecting the competition process in a given local market is costly, but it is clearly essential for (prospective) entrepreneurs to gauge the profitability of a new business initiative in that spatially-bounded context. If the entry-related costs are small and do not contemplate large non-redeployable investments on the side of the entrant, this latter can more easily adopt an 'entry and see' approach. In this respect, the small entrant obtains a (real) 'option to expand' (Dixit et al., 1994; Trigeorgis, 1996) that allows him to directly 'experiment' the perceived opportunity in the market, incurring only limited costs, but gaining more time to obtain and interpret relevant specific information (Roberts & Weitzman, 1981; Kerr et al., 2014). This safe (i.e., relatively inexpensive) 'learning sandbox', makes entrepreneurs even more determined to acquire this knowledge, and the concrete possibility to do so appears less distant from a cognitive point of view (see Reuber & Fisher, 1993; Cope, 2005). Then, small entrepreneurs have always the possibility to keep their option in staying small (or even exiting), but some of them may choose to 'kill' (i.e., exercise) the option (Folta et al., 2010; Raffiee & Feng, 2014; Gänser-Stickler et al., 2022): decide to embrace an higher degree of irreversibility, and choose to upscale their entrepreneurial endeavour, and in doing so, pursue the possibility to gain more profits (i.e., forego less profits by remaining small). In this vein, this study posits that the 'end point' in terms of responsiveness to local market conditions for this entrepreneurial process, i.e., from small to large, is the same as the one experienced by large entrants in the first place. In other terms, the dependence of large-scale entry to variables such as the different quality of the local demand segment and the spatial concentration of competitors do not differ significantly whether largeness is chosen immediately or comes later. Potential entrepreneurs are clearly heterogeneous in their initial knowledge endowment (e.g., Colombo & Grilli, 2005), in their capacity to overcome bounded-rationality limits (Simon, 1979) and they have different risk/uncertainty profiles (e.g., Barnett, 2008; Raffiee & Feng, 2014; Gänser-Stickler et al., 2022). All this heterogeneity will clearly be reflected into a different timing on the eventual choices of largeness. But we claim that what changes in these cases, given the 'learning sandbox' offered by the platform, is just the different 'timing', while the bulk of relevant 'local market' information underlying the decisions of a large-scale

of operations remains the same. Thus, the scaling up of operations through the digital external enabler will be ultimately related to sound economic forces together with the information and competences acquired during the 'learning period' as a small-scale entrepreneur, rather than being solely due to specific (innate) characteristics of individuals (e.g. Funder, 2001; Raffiee & Feng, 2014; Thorgren et al., 2016). Therefore, the empirical analyses should observe that:

HP4: Transition from a small- to a large-scale depends on the same economic variables (i.e., high-range specialization and concentration) that influence large entry in the first place.

2.3. Data & Methodologies

This section presents the empirical case for testing the conceptual hypotheses advanced in the previous section, namely the entrepreneurial phenomenon of entry on the Airbnb platform. First, it discusses why this is a relevant testbed for the arguments of this study and then it presents the Airbnb data which have been used for the analysis, also providing some descriptive statistics, the definition of the variables employed in the models, and the estimation strategies for the proposed econometric analysis.

2.3.1. Empirical Setting: Airbnb and the Short-Term Rentals Market

The hypotheses are tested within the novel short-term rental market, focusing on the digital platform Airbnb, operating in the short-term hospitality sector. In particular, other than being increasingly investigated for analysing traditional issues in the field of industrial organization (Zervas et al., 2017; Farronato & Fradkin, 2018), Airbnb has been recently exploited by researchers within the entrepreneurship literature. For example, McBride & Wuebker (2022) and Davidsson (2022) discuss the general issue of subjectivity vs. objectivity of entrepreneurial opportunities also relying on the case of Airbnb. More related to the framework of this study, and with a specific focus on Airbnb hosts, Gerwe et al. (2022) examine the differentials in entry dynamics of service providers according to the expected level of social interaction.

Airbnb and the market for short-term accommodation are a particularly suited context where to address the role of platforms as 'external enablers' of entrepreneurial actions. First, as reported in the introduction of this dissertation, and widely discussed in Chapter 1, consider that platforms like Airbnb or Uber – differently from other platforms like Amazon or eBay, that concentrate trades into single de-localized markets – help matching demand and supply into a localized area. Therefore, this type of platforms operates in a large number of well-separated different sub-markets, characterized by very different industrial, geographic, and social properties (such as different levels and compositions of entry costs, demand conditions and saturation thresholds), thus allowing the research to adopt a 'contextual entrepreneurship' view (Welter, 2011) and to understand how the enabling role of the platform in terms of entrepreneurial opportunities actually seized is shaped by specific external conditions.

Moreover, Airbnb is a perfect case where to analyse entrepreneurial incentives on very different types of entrepreneurs subject to different competitive conditions: on the one hand, competition in this industry includes a differentiated presence

of traditional entrepreneurs (i.e., hotels); on the other hand, Airbnb offers business opportunities to different kinds of entrepreneurs, captured by their scale, as suggested in the literature (see, for example, Dogru et al., 2020a). This offers the entrepreneurs a chance to easily adopt 'gradual strategies' which envisage the possibility to also observe transitions between small-scale and large-scale entrepreneurial categories.

2.3.2. Data Sources

This study primarily relies on the data provided by *AirDNA*, which offers a wealth of information on Airbnb listings and hosts. The dataset covers the period from January 2017 to December 2019; for this interval information on every active property on the entire Italian territory: location, daily reservation status and revenues are available. Moreover, each property is associated with a unique *Airbnb Host ID*, which allows to identify the number of properties that each entrepreneur manages at any given time and in any given area, and consequently individual entry dates. Property and host information has then been aggregated on a monthly basis. At this frequency the number of new entrants at provincial level (NUTS3) has then been measured, distinguishing by category of host, in terms of the number of active properties they own. On the basis of the timespan of the dataset, the analysis is, thus, confined to the period following the disruption of Airbnb, when the platform has already achieved an established role within the hospitality sector in the Italian context. For the sake of completeness, Appendix A2.1. provides the evolution of Airbnb supply side since the platform's entry into the Italian market, as well as the specification of the time-frame subject to this analysis.

Besides *AirDNA*, this chapter utilizes data from two other sources. First, *ISTAT* (the Italian National Institute of Statistics) provides several province-level variables[32] such as i) data on the capacity of tourist accommodation, measured by the number of hotels by category (identified by the number of stars) in 2011;[33] ii) data on the number of unoccupied dwellings in 2011, taken from the latest National Census; iii) data on the yearly unemployment rate; and iv) geographical time-invariant variables (average altitude and share of coastal surface). Secondly, this dataset includes data from the *Osservatorio del Mercato Immobiliare* (provided by the Italian Revenue Agency),[34] with half-yearly updates on the average monthly rent per square meter in different types of housing units.

2.3.3. The Dependent Variables: Entry of Small-Scale and Large-Scale Entrepreneurs

This analysis relies on the distinction between small-scale entrepreneurs and large-scale ones within the Airbnb domain. Dogru et al. (2020a) provide a comprehensive descriptive overview of the presence of multiple types of hosts on Airbnb. Economic literature normally uses the number of listings managed by a specific host in order to distinguish between small and large-scale ones. However, there is no consensus on a common threshold that distinguishes the two categories.[35]

[32] The complete database is accessible at http://dati.istat.it.
[33] These variables are measured considering the geographical distribution of hotels in 2011, before the entry of Airbnb on the Italian market; in this respect, the presence of traditional establishments can be considered a (non-endogenous) structural proxy of the short-term accommodation supply.
[34] See https://www.agenziaentrate.gov.it/portale/web/english.
[35] Some robustness checks using alternative thresholds will be provided in the following empirical analysis. There are several examples of thresholds used in literature for distinguishing different host types. Dogru et al. (2020a) use the quartiles of the distribution of managed properties

Therefore, this research first defines small-scale entrepreneurs as those hosts managing one or two properties and large-scale ones those managing from three to ten properties; but to verify the robustness of the findings, the analyses will always be performed using different thresholds.

[Insert Table 2.1. here.]

Table 2.1. depicts the overall distribution of hosts and properties in Italy, according to the main definition of small-scale entrepreneurs (one or two listings) and large-scale ones.[36] In December 2019 more than 240,000 different hosts were active in Italy. Most of them (86.5%) were small-scale entrepreneurs with large-scale hosts accounting for just 12.6% and the number of firms (i.e. hosts with more than ten listings) negligible (less than 1%), even if the corresponding number of listings was obviously relevant (15.5%). Table 2.2a. and Figure 2.1. illustrate the entry process of (various types of) Airbnb entrepreneurs in Italy between 2017 and 2019. According to Table 2.2a., entries of small-scale entrepreneurs dominate; however, large-scale entrepreneurs' entries are also relevant (about 0.5% per month or 6% per annum). The timing of entries (Figure 2.1.) presents a strong seasonal pattern, i.e., "hot periods" of entries which tend to slightly anticipate peak demand and shows the remarkable volatility of the entry of SSE compared to LSE (or firms).

Table 2.2b. distinguishes, for each category, the entries of brand-new Airbnb entrepreneurs from the entries of Airbnb entrepreneurs already active in other categories (SSE, LSE, or firms) or in other provinces. The evidence points to local markets which are quite separated, since the share of entries for hosts already active in other provinces is negligible for both SSE and LSE. About seven out of eight SSE entrants are brand new entrepreneurs, while most of the new LSE (about 60%) are former SSE who have decided to increase their commitment; only 25% of new LSE are genuinely new entrants. This large number of transitions from one status to the other is clearly suggestive of the important role that platforms may play as a key stepping-stone towards full-time entrepreneurship.

Then, the special character of the hosts with more than ten properties suggests excluding them from the following analyses because they are mostly established firms already active across multiple markets and subject to more complex multi-market incentives. Moreover, as seen, the number of hosts in this category is very small (even if the number of properties they manage is of course not).

The proxy for SSE vs LSE merely based on the number of listings, as said, is usual in the literature. To reinforce the meaning of that variable, the average monthly revenues associated to each category of hosts has been analyzed. Table 2.2c. clearly shows that the definitions individuate as SSE a category of entrepreneurs whose average revenue is likely to act just as additional income, while the average revenue of LSE is of the same order of magnitude as the Italian mean

in order to provide a comprehensive overview of the multi-unit hosts phenomenon on Airbnb. Kwok & Xie (2019) and Gibbs et al. (2018), in determining the pricing behavior of multi-unit hosts, distinguish between single-owners and multi-unit owners. Deboosere et al. (2019) show the differences in prices and profitability between hosts managing up to ten listings and those managing more.

[36] For the sake of simplicity, in the following tables, formulas, and text, small-scale entrepreneur is abbreviated to 'SSE' and large-scale entrepreneurs to 'LSE'.

income,[37] confirming that only this latter type of host can be reasonably regarded as a full-time entrepreneur. Furthermore, the average per-property revenue is systematically larger for LSE and much more for firms, thus also further corroborating the soundness of the empirical operationalizations of the distinction between LSE and SSE.

[Insert Tables 2.2a., 2.2b. and 2.2c. here.]

[Insert Figure 2.1. here.]

In line with this evidence, the entry variable e^{n}_{kpt}, which is the dependent variable of the models, is defined as the number of entrepreneurs from category k (k=SSE, LSE) entering Airbnb in province p, in the month t. The host is considered a SSE (LSE) if the number of properties they manage in month t in the whole of Italy is equal to or lower (greater) than n.[38]

It is worth to notice that the following issues may arise with this definition of dependent variable: on the one side there is the risk treat as new entrant hosts that were already active on Airbnb and then delisted (e.g., seasonal properties), on the other side treat as new entrant hosts who already offer a hospitality services within the local sub-market through different channels that the data at disposition are not able to measure. However, it is possible to conservatively assume that both issues are minimized since: a) Airbnb allow hosts to block their calendars (i.e., they can interrupt the availability of a specific property for a – short or long – period) without delisting and with no cost (thus without losing reviews and evaluations too), b) the following regression models controls for the total number of hotel beds of the sub-market to account for the potential measurement error within the dependent variable, and c) Airbnb in the period under exam was already well-diffused in Italy, with a (rather uniform) majority market share in every sub-market, since Airbnb already captured most of the market shares of the other platforms or alternative channels..

In line with this dependent variable, the variable $TRANS^{n}_{pt}$ and NEW_{kpt} are defined and tested in further econometric models. In particular, while $TRANS^{n}_{pt}$ depicts the number of SSE switching to an LSE status according to a threshold n (i.e., when the number of listings managed increases from n to n+1) in a market p at time t, NEW^{n}_{kpt} counts the number of entrepreneurs of type k (k = SSE, LSE), as defined with a threshold n, entering for the first time the Airbnb platform in a market p at time t.

2.3.4. Demand, Spatial Concentration of Supply and Opportunity Costs

Greater demand for accommodation in a specific region means, ceteris paribus, greater profitability and thus a greater incentive to enter (see HP1). How and when potential entrepreneurs obtain this information is not obvious. This study measures the demand climate perceived by the entrepreneurs in a specific month t as the cumulative amount of Airbnb reservations in that area in a time interval around t. This variable actually represents an equilibrium quantity rather than a proper demand variable, but it is the easiest signal of the number of business opportunities on Airbnb a prospective

[37] For reference purposes, the monthly average households income in Italy in 2018 has been equal to € 2.637 (source: European Union Statistics on Income and Living Conditions).

[38] A similar variable defining entry, still considering single-unit hosts only, but distinguishing between entire apartments and shared accommodations, has been used by Gerwe et al. (2020) to account for different levels of social interaction between hosts and guests.

entrepreneur can directly observe. In this sense, it is worthwhile to note that reservations normally significantly anticipate the overnight stay, so that reservations in the near future (see below) are actually directly observed with little uncertainty.

Consistently, the variable $MarketClimate^{f}_{pt}$ is defined as follows in Eq. 2.1.:

$$\mathrm{MarketClimate}^{f}_{pt} = \sum_{i=t-f}^{i=t+f} \mathrm{ReservedNights}_{pi} \Big/ 2f+1$$

(Eq. 2.1.)

where $2f+1$ is the length (in months) of the interval centered around t. $ReservedNights_{pi}$ is the number of reserved nights on Airbnb in province p and a given month i (which is comprised in the interval between $t-f$ and $t+f$). The MarketClimate variable, defined as a moving average, also allows to smooth easily predictable seasonal effects. In line with descriptive statistics on AirDNA data, the value of f is fixed at 3 since 72% of reservations in the dataset have been reserved within 90 days of the overnight stay.[39] Still, given the uncertainty which could affect the value of f and to account for possible endogeneity into the econometric specification, a robustness check employing an alternative definition of market climate is proposed in the section dedicated to robustness checks.

Alongside the quantitative definition of (prospective) demand, this study is also interested in its qualitative nature (see HP2b). To this end, the metric $HighQuality_{p}$ is thus defined as the percentage of higher-quality hotel beds (namely hotels with four, five, and five luxury stars) available in market p. As mentioned, this metric is calculated according to traditional hospitality distribution before the entry of Airbnb (i.e., in 2011), thus assuming that the market share of higher-quality hotels is a good proxy of the expected quality of accommodation services in province p. In order to distinguish markets according to the expected quality of their accommodation service, this study employes the dummy variable $HighRangeSpecialized_{p}$ which is equal to one if the metric $HighQuality_{p}$ is above the sample median, zero otherwise.

Opportunity costs are proxied by i) the number of unoccupied dwellings in province p, $UnoccupiedDwellings_{p}$, and ii) the unemployment rate in province p at time t, $UnemplRate_{pt}$. Following Dogru et al. (2020b) and Gerwe et al. (2020), HP2a predicts that the higher both unoccupied dwellings and unemployment, the lower the opportunity costs perceived by individuals in the local market for entering the Airbnb platform as hosts, and in turn this should positively affect the entry of non-professional entrepreneurs (i.e. SSE) more than the entry of professional ones (i.e. LSE).[40]

Spatial density of the supply encompasses the effects of proximity discussed in the theoretical section (i.e. A. information, B. cluster and C. competition effects). In particular, $ConcentrationProp_{pt}$ is defined as the number of active properties in

[39] The average lag between booking date and overnight stay in our sample is 71.1 days (with a standard deviation of 84.4 days), while the median value is 39 days. These statistics have been calculated on the basis of the availability of booking dates and overnight stay dates per each reservation booked in Italy on Airbnb within our time span.

[40] These proxies for the opportunity costs of time and physical assets are likely to be correlated with the demand for accommodation. In fact, i) the number of unoccupied dwellings (which is used as a proxy for an excess of supply in the residential rental market) also indicate a relevant presence of second homes, i.e. the touristic vocation of the area, and ii) the unemployment rate (that is used as a proxy for depressed labour market conditions) is higher where a poor demand for business tourism services is expected. Both variables can then be only considered as proxies of the level of opportunity costs *ceteris paribus*, i.e. after controlling for the perceived market demand (*MarketClimate*).

province p during month t per surface unit.[41] This variable (and its quadratic term) will be instrumental for the testing of HP3a and HP3b.

2.3.5. Econometric Approach

This analysis aims to estimate the entry dynamics of both SSE and LSE and investigate whether their patterns are driven by different mechanisms. For this aim, a panel dataset on the number of monthly net-entries (e^n_{kpt}) of both SSE and LSE has been constructed. The impact of the different locally-bounded market and geographical variables is tested by estimating the following Eq. 2.2.:

$$\begin{aligned} e^{n}_{k,p,t} = \ & \alpha_0 + \ \alpha_{1,k} e^{n}_{k,p,t-1} + \ \beta_k \ln\left(\text{MarketClimate}^{3}_{p,t}\right) + \delta_{1,k}\text{UnoccupiedDwellings}_p \\ & + \delta_{2,k}\text{UnemplRate}_{p,t} + \delta_{3,k}\text{HighRangeSpecialied}_p + \ \gamma_{1,k}\text{ConcentrationProp}_{p,t-1} \\ & + \gamma_{2,k}\text{ConcentrationProp}^{2}_{p,t-1} + C_{p,t} + \ M_t + \ T_t + \mu_p + \ \varepsilon_{p,t} \end{aligned}$$

(Eq. 2.2.)

The dependent variable is the natural logarithm of the number of net entries e^n_{kpt} of SSE or LSE in the province p ($p = 1 \dots 107$) and month t during the time-period 2017 to 2019,[42] as previously defined. The net entries of Airbnb hosts are estimated according to a set of independent variables including:

i) e^n_{kpt-1} that is the one period lag of the dependent variable;

ii) ln(MarketClimate $^3_{pt}$), that is the natural logarithm of the market climate;

iii) UnoccupiedDwellings $_p$, UnemplRate $_{pt}$ and HighRangeSpecialized $_p$ are respectively the log-transformed actual number of empty dwellings, the yearly unemployment rate and the dummy variable representing a higher presence of four, five, and five luxury star hotels in province p;

iv) ConcentrationProp $_{pt-1}$ and ConcentrationProp^2 $_{pt-1}$ are respectively the linear and the quadratic terms of concentration;

v) $C_{p,t}$ is a set of additional controls. Firstly, $C_{p,t}$ includes housing market conditions with the average monthly rent per square meter of residential units in province p since the conditions on the real estate market are expected to influence the entry processes in Airbnb (Gerwe et al., 2020).[43] Secondly, it controls for the province's morphological characteristics which can influence the attraction of market p to tourists. In particular, it includes the average altitude of the province[44]

[41] *ConcentrationProp* is a measure of supply density. A measure of entrepreneur density (as the number of hosts per surface unit) has been also tried and these analyses produced very similar results to those that will be shown.

[42] Values have been augmented by one unit since there are few cases in which our dependent variable has a value of zero.

[43] *Osservatorio del Mercato Immobiliare (OMI)* data is released at a sub-city level (OMI zones) on a half-yearly basis. It provides the minimum and maximum monthly rent per square meter for different types of residential and commercial units. The variable is computed as the mid-point between average minimum and average maximum rents (only considering dwellings, apartments and villas) in each specific province.

[44] *ISTAT* releases data on the average altitude at municipal level; the average altitude variable at provincial level is the sum of municipal altitudes weighted according to surface.

and the percentage of municipalities with a coastal location[45]. Finally, $C_{p,t}$ controls for the relevance of the traditional hospitality supply with the number of hotel beds as of 2011.[46] All continuous variables (excluding ratios) are in natural logarithms. Finally, to control for potential heterogeneity over time in our data, month dummies ($\mathbf{M_t}$) to account for seasonality, and a time-counter ($\mathbf{T_t}$) to control for trends have been included.

[Insert Table 2.3a. here.]

[Insert Table 2.3b. here.]

Table 2.3a. shows a brief overview of the definition of the variables, while Table 2.3b. provides descriptive statistics for the dependent, independent, and control variables. Throughout the econometric analysis presented in the next section, the evidences will be provided according to two different specifications of SSE and LSE (namely SSE owning one to two listings or one to three listings, and LSE owning three to ten or four to ten listings). Other specifications are reported in the robustness checks section.

Ex-ante, in line with the theoretical hypotheses formulated, it is expected to find the coefficients β_k (MarketClimate$^3_{pt}$) to be positive and significant for both kind of entrepreneurs (HP1), the coefficients $\delta_{1,k}$ (UnoccupiedDwellings$_p$) and $\delta_{2,k}$ (UnemplRate$_{pt}$) to be positive and significant for SSE and greater than those affecting the entries of LSE (HP2a), and the coefficients $\delta_{3,k}$ (HighRangeSpecialized$_p$) to positively impact the entry of LSE rather than the entries of SSE (HP2b). Turning to the third set of hypotheses (HP3a/b), the sign of the coefficients γ_1 and γ_2 (respectively the coefficients of ConcentrationProp$_{pt-1}$ and ConcentrationProp$^2_{pt-1}$) is expected to be positive and negative for LSE and both statistically significant, suggesting that professional Airbnb hosts are sensitive to the three effects of spatial concentration as defined in the theoretical section. Conversely, the same coefficients for the regressions on SSE should not be statistically significant. HP4 suggests that transitions from a small- to a large-scale will be determined by the same economic variables (high-range specialization and concentration, in particular) that influence large-scale entries. This hypothesis will be tested by comparing the coefficients for the regressions on small-scale entrepreneurs entering the large-scale category, represented by tnpt, with the coefficients for the regressions on brand-new large-scale entrepreneurs, namely newnLSEpt.

Finally, note that the specification of Equation 2.2. includes the lagged dependent variable to better account for the persistence of the dependent variable over time (see Nickell, 1981 among others); but at the same time, this type of specification introduces a potential dynamic panel bias which may lead to biased estimates. In fact, the lagged dependent variable e^n_{kpt-1} is correlated with the cross-sectional part, μ_p, of the error term, and hence endogenous. As is customary, in order to tackle the problem, this study adopts the GMM-SYS approach (Arellano & Bond, 1991; Blundell & Bond, 1998) to corroborate the random-effects estimates. The GMM approach has already been adopted in Airbnb literature: Dogru

[45] Both control variables have been included because the aim is to control for the presence of seaside or mountain touristic attractions in a given sub-market. This is particularly important, because natural amenities can affect both demand and entries of service providers into the Airbnb platform. It is worth to notice that there are sub-markets that are neither coastal or mountain, confirming the importance of these control variables.
[46] Similar to the definition of the variable *HighQuality*$_p$, this control refers to the number of hotels beds in 2011 in order to limit possible endogeneity concerns.

et al. (2020b) use a GMM-SYS model in order to estimate which macroeconomic factors lead to the diffusion of the short-term rental platform; while Benitez-Aurioles & Tussyadiah (2020) adopt the same econometric approach for estimating the causal relationship of Airbnb on house rentals and purchases. The Blundell-Bond estimators employed in this study (under the columns GMM-SYS in Tables 2.4. and 2.5.) uses a curtailed instrument set, with moment conditions in the intervals [t-4; t-5] to instrument $e^{n}_{SSEpt-1}$ and [t-3; t-4] to instrument $e^{n}_{LSEpt-1}$. These moment conditions have been chosen according to the AR(#) tests to avoid endogeneity in the instrument sets caused by serial correlation. The use of a restricted instrument set is justified by the fact that using all available past observations of e^{n}_{kpt-1} would potentially lead to distorted estimates caused by overidentification (i.e. the instrument proliferation problem, see Roodman 2009).[47]

Moreover, the two-step estimation is applied and the estimator adopts the finite-sample Windmeijer (2005) correction for the covariance matrix. All estimates (both random effects and GMM-SYS) are based on robust standard errors.

2.4. Results.

2.4.1. Main Results: Overall Entry Determinants

Tables 2.4. and 2.5. report the results of the estimates. Equation 2.2. is estimated for two different thresholds of SSE and LSE (i.e., entrepreneurs owning from one to two listings or one to three listings, and, complementarily, those owning three to ten or four to ten listings). The first column per each category of entrepreneur provides the results of the random effects estimates, while the second provides the results of the GMM-SYS ones, estimated through the Blundell & Bond (1998) estimator previously described. The random effects and GMM-SYS estimates are rather similar, with the same sign and levels of statistical significance for all the independent variables across the two methods. Consequently, the discussion on the magnitude of the coefficients will focus on the GMM set of estimates. Moreover, results are robust when comparing the two definitions of both SSE and LSE, confirming the outcomes of our analysis regardless of the threshold n in the dependent variable e^{n}_{kpt}. Further robustness checks on this specific aspect will also be run in the dedicated subsection. Unsurprisingly, the lagged dependent variable is always positive and statistically significant (with coefficients far below one), confirming the dynamic relationship in the entries of potential Airbnb entrepreneurs postulated in the econometric models[48].

[Insert Table 2.4. here.]

[47] Note that in all GMM-SYS estimates the ratio between the number of instruments and the observations is far below one (0.04). Moreover, the Hansen Test for Overidentifying Restrictions, besides not rejecting the null hypotheses of instrument validity in all estimates, never displays the implausible *p*-value of 1.000 or closer (which may easily occur when the number of instruments is too large) suggesting that the restriction in the number of instruments correctly avoids instrument proliferation issues. Furthermore, this *p*-value is always in line and comparable with those suggested by Roodman (2009).

[48] To this extent, it is worth to acknowledge that the R2 of the models is high. An additional inspection to understand why such values are higher employing the Shapley Value competitive decomposition of the R2 (Chavez Juarez, 2012) has thus been conducted. The decomposition shows that more than 30% of the R2 in small-scale entrapreneurs' entries equation and 26% of large-scale entrepreneurs' entries equation are explained by the lagged dependent variable. Appendix A2.2. provides the tables in support of this decomposition.

In line with the expectations and with the literature on network externalities in multi-sided markets (Hagiu, 2007; Parker & Van Alstyne, 2005), Table 2.4. confirms HP1 showing that, with all else being equal, perceived demand positively affects the entry rates of both SSE (β_{SSE} varies from +0.5083 to +0.5194) and LSE (β_{LSE} varies from +0.3318 to +0.4714) confirming that the variable is a significant predictor in determining the entries of both types of entrepreneurs. Indeed, the results show that, on average, a 10% increase in MarketClimate $^{3}{}_{pt}$ is associated with a 4.96%-5.07% increase in SSE entries and a 3.21%-4.60% increase in the entry of LSE, both significant (with p=0.000).

Considering the proxies for the role of opportunity costs – the stock of unoccupied dwellings and the rate of unemployment – they both behave in the postulated directions, showing that tighter labor market conditions and the diffused availability of empty dwellings predict ceteris paribus – i.e., for a given level of common "market demand" – a stronger incentive to entry for gig entrepreneurs. According to HP2a, a 10% increase in the stock of unoccupied dwellings is, indeed, significantly associated with a 1.51% increase in SSE entries, while the relationship is not significant for the entries of LSE ($\delta_{1,\mathrm{SSE}}$ varies from 0.1569 to 0.157, while $\delta_{1,\mathrm{LSE}}$ is not significantly different from zero). Conversely, a one percentage point increase in the rate of unemployment has a significant effect on the entries of both SSE (1.67%-1.70% increase in entries) and LSE (1.59%-2.59%), as both coefficients are significantly different from zero (p varying from 0.000 to 0.004). In line with HP2b, the high-range specialization of the tourism industry significantly affects only the entries of LSE (8.83%-9.45% higher entries) as opposed to those of SSE.

[Insert Table 2.5. here.]

Table 2.5. provides the full model including the one period lag of supply concentration.[49] The new independent variables of interest, related to the local concentration of supply, show significantly different effects for the two different types of entrepreneurs. HP3a states that, all else being equal, concentration significantly affects the entry of LSE rather than SSE, leading to HP3b which postulates that the relationship between concentration and LSE entries follows a bell-shaped curve as a consequence of the interdependence of the various effects of concentration discussed in the theoretical section. The results in Table 2.5. confirm the hypotheses. On the one hand, the relationship between concentration and the entries of SSE is not significantly different from zero, both in linear and quadratic terms (see the coefficients $\gamma_{1,\mathrm{SSE}}$ and $\gamma_{2,\mathrm{LSE}}$). On the other hand, LSE entries are significantly (p in the range within 0.001 and 0.005) affected by concentration both in linear terms, with positive coefficients varying from +0.1138 to +0.1293 (respectively in GMM-SYS estimates for $e^{2}{}_{LSEpt}$ and $e^{3}{}_{LSEpt}$), and quadratic terms, with negative coefficients varying from -0.0061 to -0.0072 (respectively in GMM-SYS estimates for $e^{2}{}_{LSEpt}$ and $e^{3}{}_{LSEpt}$).

[49] Note that all evidence reported in Table 2.4. is fully confirmed in Table 2.5. when the variables $ConcentrationProp_{pt-1}$ and $ConcentrationProp^{2}{}_{pt-1}$ are included in the model.

2.4.2. Carrying Capacity, Large Scale Entrepreneurs Entries and Concentration

The signs of the coefficients $\gamma_{1,\mathrm{LSE}}$ and $\gamma_{2,\mathrm{LSE}}$, both significant at 1% confidence level and respectively positive and negative, highlight the presence of a non-linear concave impact of the concentration of supply on the entries of LSE. These results lead to the postulated bell-shaped curve in Figure 2.2. representing the concave relationship between industry concentration and middleman entries hypothesized in HP3b.[50] In other words, the concave relationship shows that, up to a specific threshold, increases in concentration positively affect the entries of middlemen, while, when the threshold has been reached, the deterring effects prevail, discouraging entries. Table 2.6. shows the predicted values of the turning point (i.e., the maximum) of the bell-shaped curve according to the GMM-SYS estimates of Table 2.5. To the extent that the maximum of ConcentrationProp $_{pt-1}$ is a representation of the optimal market capacity for Airbnb potential entrants (still recognized only by middlemen), the results show that on average, when in the average province the supply concentration exceeds the threshold of 8.95-9.33 properties per squared kilometer, an increase in the stock of active properties has a negative effect on the entries of LSE.

[Insert Figure 2.2. here.]

[Insert Table 2.6. here.]

2.4.3. Long-Run Effects

Based on the estimates in Table 2.5., it is possible to compute the long-run effects of the linear variables in the model. In particular, the Long-Run Propensity (LRP) of an independent variable in a dynamic model is (see also Reed & Zhu, 2017):

$$\mathrm{LRP}_{\mathrm{b,k}} = \frac{\mathrm{Estimate}_{\mathrm{b,k}}}{(1-\alpha_{1,\mathrm{k}})} \qquad \text{(Eq. 2.3.)}$$

where Estimate $_{bk}$ is the estimated coefficient for an independent variable b (b = MarketClimate ^{3} $_{pt}$, UnoccupiedDwellings $_p$, UnemplRate $_{pt}$ and HighRangeSpecialized $_p$) and $\alpha_{1,\mathrm{k}}$ is the coefficient of the lagged dependent variable (k = SSE, LSE).[51] Table 2.7. provides estimates for the long-run effects as well as a comparison with the short-run effects already reported in Table 2.5. The Table shows that, in the long-run, a 10% increase in MarketClimate ^{3} $_{pt}$ is associated with a 5.79%-5.84% increase in SSE entries and a 4.14%-5.09% increase in the entries of LSE, with both effects significant at the 1% level. Similarly, the long-run effect of a 10% increase in the stock of unoccupied dwellings is an increase of 1.87%-1.89%

[50] Figure 2.2. shows the marginal predicted values of e ^{2} $_{kpt}$ according to different values of ConcentrationProp $_{pt-1}$. The marginal predicted value is calculated varying the ConcentrationProp $_{pt-1}$ variable from 0.05 to 15.97 (see Table 2.3.), while all the other model's covariates are kept at their respective mean.

[51] According to Reed & Zhu (2017) the estimate of the long-run propensity (LRP) is not exempt from methodological issues. Issues arise when: i) the estimate of $\alpha_{1,k}$ is biased by the finite sample bias (Nickell, 1981), and ii) the coefficient $\alpha_{1,k}$ is close to one. Still, the adoption of the GMM-SYS methodology (Blundell & Bond, 1998) to tackle the endogeneity within the specification and a $\alpha_{1,k}$ coefficient well below one, makes the presented estimates of LRP reliable.

in SSE entries, while no significant deviations are observed for LSE. The long-run impact of unemployment is significant for both SSE (1.93%-2.04% increase in entries per each percentage point increase in unemployment) and LSE (2.69%-3.32% increase in entries). Finally, the results find that high-range specialized markets foresee in the long-run a 10.76%-17.48% increase in LSE entries (respectively significant at the 10% and 1% level), while no significant effects are found for SSE.

[Insert Table 2.7. here.]

2.4.4. Staged Large Scale Entry

Other than acting as external enabler, providing and creating opportunities for prospective entrepreneurs, the theoretical background has postulated that one of the main characteristics of platforms is the fact that they allow entrepreneurs to opt for an hybrid and gradual approach. In other words, as clearly shown in Table 2.2b., the platform allows potential entrepreneurs to gradually test their offering, first starting with an hybrid approach to the platform (in the sense of Folta et al., 2010), and then decide whether to upscale or not the financial and time commitment into more professional and structured entrepreneurial activities. To this extent, building upon the same methodological choices as in the previous models, this section shows the determinants of staged large-scale entries (called $TRANS^{n}_{pt}$), i.e., the determinants of status transitions from SSE to LSE, comparing them with the determinants of brand-new LSE entries (called NEW^{n}_{LSEpt}).

[Insert Table 2.8. here.]

Table 2.8. provides the estimates for staged large scale entries and brand-new LSE for the thresholds n equal to 2 or 3, showing also in this case the random effects and the GMM-SYS estimations. As shown, the two dependent variables present the same dynamics, namely both staged LSE entries and brand-new LSE ones are driven by the same local economic variables. In particular: a) they are both demand driven, b) they are sensible to economic conditions of unemployment, c) they are significantly driven where higher quality of touristic services is expected (i.e., confirming that it is more likely to observe brand-new professionals and professionalization mechanisms in high-end markets), and more importantly, d) transitions and brand-new entries both follow a quadratic bell-shaped curve in relationship to the local supply concentration. In this sense, these results, beyond confirming the hypothesis HP4, additionally envisages that the platform, other than being an external enabler, can act as a nursery for potential entrepreneurs who gradually approach the market with limited time and effort.

2.4.5. Robustness Checks

A large battery of robustness checks has been conducted in order to corroborate the results: for this purpose, the thresholds and definitions of the main variables have been modified in multiple ways. At a glance, the results in Tables 2.4. and 2.5. are robust and are not affected by the operationalization of different variables including i) a different threshold defining SSE and LSE, ii) a different specification of the variable MarketClimate, iii) a different specification of concentration, iv) a different estimation methodology, and v) concerns related to the spatial structure of the data.

As already mentioned, there is no unanimously shared threshold in literature for distinguishing gig entrepreneurs from middlemen (see again, for instance, the various contributions from Dogru et al., 2020a; Kwok & Xie, 2019; Deboosere et al., 2019). Given the various nature of Airbnb listings, hosts managing multiple units may handle multiple parts of apartments (or rooms) simultaneously within the same accommodation (i.e., listing type is "Private Room" or "Shared Room"), or different accommodation (i.e., when the listing type is "Entire Apartment"). To deal with this potential source of error, the analyses have been tested on a wider definition of SSE, thus considering those managing up to four listings (*n* equal to 4 in e^{n}_{kpt}) as opposed to LSE managing from five to ten listings simultaneously. Furthermore, the estimation results for SSE as defined by *n* equals to 1 has been also included. Estimates are reported in the Appendix A2.3. and all results discussed so far are confirmed.[52]

To the extent that the estimates shown in Tables 2.4. and 2.5. might be impacted by alternative definitions of the variable capturing market climate, and given that per each reservations, both the booking date and the overnight stay date are known, two additional alternative specifications for such variable have been used: i) $\text{DemandFuture}_{p,t}$ which is equal to the number of reservations in province *p* already accepted at time *t* for dates from *t* onwards, and ii) $\text{DemandFutureF}_{p,t}$ which is equal to the number of reservations in province *p*, already accepted at time *t* for dates from *t*+1 onwards. In line with the definition, these measures do not depend on the discretionary value of the parameter *f*; moreover, by including them in a GMM-SYS estimate which accounts for the endogeneity of past lags of the dependent variables, they are exogenous by definition given that they are uncorrelated with future values of entrepreneurial entries at the local level. Appendix A2.4. provides the results, showing that the findings are fully confirmed by these new proxies for market climate.

From a theoretical viewpoint it is known that, with demand being equal, entries are normally higher where competition is mild. By contrast, when a suitable level of concentration is reached (i.e., the carrying capacity of Carree & Thurik, 1999, and Haynes & Thompson, 2013), entries are discouraged. The former results confirm HP3a/b suggesting that professional entrepreneurs are more aware of all the effects of concentration, leading to the bell-shaped curve depicted in Figure 2.2. Still, to test the deterrent effect of higher concentration (i.e., competition) on entries, Eq.2.2. has been also estimated by inserting a dummy variable ($\text{ConcOverMedian}_{pt}$) equal to one when concentration is over the sample median (0.35) rather than the continuous values $\text{ConcentrationProp}_{p,t-1}$ and $\text{ConcentrationProp}^2_{p,t-1}$. Results in Table A2.5. in the Appendix have similar patterns to those in Tables 2.4. and 2.5. showing that SSE are neither positively nor significantly affected by *higher* concentration, while LSE entries are discouraged (with statistically significant coefficients or nearly significant at 10% confidence level).

[52] A stricter definition of LSE, defining e^{n}_{kpt} with *n* equal to one, complementing the one in A2.3. for SSE, has also been tested. In this case, find large-scale entrepreneurs are not significantly affected by concentration (both in linear and quadratic terms). It is likely that such a strict definition strengthens the results as, with this specification, the LSE entries include a large share of hosts managing a very low number of properties (i.e., two properties) who, accordingly, cannot really be defined as true "large-scale". Furthermore, Tables 2.4., 2.5. and A2.3. show that the significant impact of concentration remains stable as *n* increases.

Additionally, an alternative estimation methodology, i.e., a traditional static model, adopting a pooled OLS with robust standard errors clustered at the province *p* level is provided. Results are shown in Appendix A2.6. in and have similar patterns to those reported in the main Tables 2.4. and 2.5.

Finally, the robustness of the results has been also tested according to the spatial structure of the data. In particular, two main issues may arise. On the one side, our definition of sub-market (i.e., NUTS3) may be too large, being relevant markets much smaller. On the other side, although the temporal dynamics within the data has been correctly modeled by the means of GMM-SYS estimation, spatial correlations between contiguous markets can be relevant, thus influencing the estimates. Appendix A2.7. provides multiple tables supporting the robustness of our results. Appendixes A2.7a. and A2.7b. confirms that, although the relevant market can be small in some cases, the issue is well controlled in the empirical setting as the presence of Airbnb within Italian NUTS3 is typically concentrated in the central market (see A2.7a.). Furthermore, the hypotheses have been also tested leaving out from the estimation sample the sub-markets of Rome, Florence, and Naples, which are, at the best of the author's knowledge, multicentric sub-markets. Consistently, very similar results to those reported in Tables 2.4. and 2.5. are found (see A2.7b.). Appendixes A2.7c. provides an alternative estimation procedure, introducing a queen-contiguity spatial weight matrix W in the model[53], thus including as additional independent variable the *MarketClimate* which pre-multiplied by W. The results are robust to the inclusion of the spatial component. Furthermore, Table A2.7c. shows that the entries in a sub-market are not significantly affected by demand in contiguous provinces (either for SSE or LSE), thus confirming the background assumption that sub-markets are separated[54].

2.5. Discussions and Conclusions

This study examines the extent to which specific local market conditions influence the possibility of an external digital enabler of entrepreneurship to generate entrepreneurial acts in that specific market context. In pursuing this objective, entrepreneurs are differentiated according to their scale of entry, and in parallel, the local market determinants of their eventual transition from a small to a large scale of operations are analyzed. A series of hypotheses are tested on the sharing economy platform Airbnb and on the respective hosts recorded in Italy between 2017 and 2019.

Airbnb platform offers a wide range of entrepreneurial opportunities to different types of agents (Dogru et al., 2020a): *small entrepreneurs*, i.e. hosts renting out their own apartment (or a room in their apartment), and relatively *large entrepreneurs*, i.e. hosts managing multiple properties at the same time. The results of the analysis show that if the two typologies are equally stimulated by the size of (perceived) demand and by labor market conditions, LSE entry is much

[53] To the extent that it is required to properly model the spatial relationship, the lagged dependent variable has not been included within the regressors.

[54] A traditional spatial autoregressive model has also been tested, where the dependent variable (pre-multiplied by W) has been included as regressor. Other than confirming the results, a spatial autocorrelation of entries (for both small and large scale entrepreneurs) is found. This additional evidence can be interpreted as consequence of contiguous morphological conditions which shape the patterns of entries.

more sensitive to supply-side characteristics and to the quality of demand (i.e. high-range specialized markets), while lower opportunity costs in the local market seems to spur on small rather than large entrepreneurial acts. Pairing this finding with the insensitivity of small entrepreneurs' decisions with respect to level of local supply leads to a possible *oversupply*, such that small-scale entries are not discouraged even if local competition is already strong. By contrast, large scale entries are significantly responsive to market concentration at local level, such that the relationship between entry and concentration follows a bell-shaped curve (see Figure 2.2.), as a sound economic reasoning implies. In fact, agglomeration effects, locally-bounded information mechanisms and competition effects are all at work. On the one side, at lower levels of concentration the information and cluster effects make entrepreneurs aware of the business opportunities and allow them to benefit from proximity which consequently leads to increased product differentiation for potential customers. The combination of these two effects is predominant in the first part of the bell-shaped curve. On the other side, when the supply level is sufficiently high, the competition effects prevail over information effects (which gradually lose their informative potential), discouraging entry. All this economically-reasoned entry process is only perceived by large entrepreneurs, while the entry of small entrepreneurs is found to be almost only demand-pull. Finally, the results also highlight the relevant tendency to pursue large scale entrepreneurial activities through an external digital platform enabler with a *gradual* approach: in fact, the majority of large entries are indeed staged entries, i.e., which started from a small scale to eventually scale up. Interestingly, the dynamics of these staged entries is governed by the same economic forces which determine immediate large entries.

These results can contribute to various streams of entrepreneurship literature.

Firstly, they highlight the importance to contextualize the "external enablement" potential of a sharing economy platform in the plenty of different local market contexts where the platform is deployed. Entrepreneurial opportunities brought in by sharing economy platforms are clearly not evenly distributed across territories, and they are here found to be significantly shaped by local market conditions. In this way this research increases the understanding of the interrelationships accruing between the enabler and its (market) context, by enriching the "external enablement" literature of an important insight, and by furtherly emphasizing the importance of contextualizing this nascent stream of the literature.

Secondly, this study adds to the hybrid entrepreneurship literature by showing how the scale of the seizing of entrepreneurial opportunities through digital peer-to-peer platforms is highly sensitive to market factors. In line with Nambisan et al. (2018), it shows that, according to the different levels of commitment and investment, there are various ways to pursue entrepreneurial opportunities in a platform-based economy, where different entry approaches are not mutually exclusive. In line with competitive selection models (Jovanovic, 1982), small-scale entrepreneurial acts can represent a stepping-stone towards relatively larger and probably more intensive forms of businesses (Folta et al., 2010; Raffiee & Feng, 2014), and the descriptive evidence confirms that most of the large entries through the platform have been originated by previous small scale experiences. At the same time, the econometric results highlight how the scale

of entry is indeed influenced by different drivers, but when transitions from small to large occur, these latter are governed by the same local market factors which impact large entry in the first place. Thus, this study unveils a potential role for an external digital platform enabler as a relatively unexpensive 'learning sandbox' for prospective entrepreneurs. By giving them unlimited time to 'stay' in the market at a very low cost, these sharing economy platforms can also offer entrepreneurs the opportunity to learn at their own pace, reducing the probabilities of "unreasoned" large entries.

Finally, analogously to Gerwe et al. (2020), this study expands the literature on the determinants of growth of a sharing economy platform. As to network effects, the perception of same side and cross-side externalities are clearly crucial in determining the decision to join platform markets. Nevertheless, it is possible to notice that these factors can be differently perceived by different kinds of hosts according to their scale of involvement in the platform business. Being equally stimulated by local demand, which could adequately approximate cross-side externalities (Eisenmann et al., 2006), this study shows that local levels of concentration, representing same-side externalities within the supply, are not perceived in the same manner by all providers. More specifically, the analysis shows that for a small provider, same-side externalities can be rather low; while for large ones, same-side externalities may be positive for a relatively low number of peers before becoming negative for a larger number of "competitors". Thus, in addition to the industry growth rate (as shown in Gerwe et al., 2020), the local level of demand is also an important predictor of entrepreneurial entries, but supply conditions matter more for relatively larger entrepreneurs, while lower opportunity costs perceived at local level favor the entries of small entrepreneurs into the platform.

2.5.1. Limitations and Future Research

The study is clearly not immune from limitations which may open avenues for future research in both the external enabler and hybrid entrepreneurship streams of literature. Firstly, the results cover the time span between January 2017 and December 2019, thus the time-window we observe stops just before the Covid-19 pandemic. This way the results are unaffected by this negative exogeneous shock. At the same time, the Covid-19 pandemic is considered another important external enabler for entrepreneurship (e.g. Davidsson et al., 2021; Lucas & Bellavitis, 2022), and while the pandemic has undoubtedly negatively affected the whole tourism sector, it would be interesting to investigate how one enabler has affected the other in different local markets, i.e., how the net result in terms of entrepreneurial activity has been shaped by specific local market conditions. Secondly, the analyses on the determinants of transitions of entrepreneurs from a small to a large scale look at the local market factors, given the focus of the present study. While human agency has been clearly found relevant to explain such dynamics (e.g. Wennberg et al., 2006; Folta et al., 2010; Raffie & Feng, 2014) the way human factors (e.g. demographic and pshcological traits, human capital charcateristics of individuals) interact with the local market context to explain the transition process has never been explored so far, while it could clearly reveal much more insights about the cognitive mechanisms that lead some individuals (and not others) to scale up their entrepreneurial endeavor in a given specific market.

2.5.2. Managerial and Policy Implications

The findings of this study have also a series of interesting implications for different stakeholders. Managers of sharing economy platforms learn how content providers of different scales respond to different market stimuli but how, at the same time, in a dynamic perspective, they are certainly not separate silos. However, this has two implications. First, small suppliers can at least partly crowd out the relatively largest ones. To the extent that the professional figure is the most remunerative for platform managers (Deboosere et al., 2019; Kwok & Xie, 2019), and that scale of operations is a good proxy for this professionalism, being able to neutralize excessive entry by small suppliers and/or ease their transition towards large scale can be of crucial importance for platform managers to ensure the survival and profitability of their two-sided business. Secondly, and connected to this, nudging the quality besides the quantity of local demand can be an important leverage to attract large users on the supply side.

Then, individuals who are considering becoming entrepreneurs using these platforms are informed about the importance of considering the characteristics of submarkets. As long as indirect (cross-side or same-side) network externalities are locally bounded (Stallkamp & Schotter, 2021), large entry into this type of business requires an in-depth investigation of the actual structural conditions on which local competition will take place. At the same time, this study documents how prospective entrepreneurs can pursue a *staged* approach, where these external digital platform enablers can actually act as rather inexpensive "learning sandboxes"; because in the end, transitions are governed by the same sound economic logic (as it is predicted by economic theory) that determines large entry in the first place.

Finally, there may also be instructive implications for policymakers. As a matter of fact, the analysis does not support general economic equilibrium considerations for either the tourism sector or the economic system as a whole. But the fact that entrepreneurial acts made possible through the external enabler, irrespective of their scale, are more likely to emerge in areas with high unemployment rates is worthy of reflection, especially if this finding is combined with the evidence that platforms are not found to crowd out the overall quality of the entrepreneurial activity in an area (Burtch et al., 2018). As a matter of fact, none of these entrepreneurial phenomena, whatever their professional nature, have been policy-induced, i.e., they are endogenous and likely originated spontaneously as a response to the lack of employment alternatives for citizens or in the presence of a higher stock of idle or underutilized assets (in the case of small-scale entries). Therefore, to the extent that negative spillover effects towards other sectors are limited, local policymakers should consider that the external enablement function towards entrepreneurship brought in by sharing economy platforms, while potentially representing a threat for vested positions in markets, could also be a new (rather exogenous) arrow in the quiver of local economic development policies.

References – Chapter 2

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Tables – Chapter 2

Table 2.1. Distribution of Airbnb entrepreneurs among small-scale, large scale and firms.

		Small-Scale Entrep. (1-2 listing)	Large-Scale Entrep. (3-10 listings)	Firms (+11 listings)	Total
Hosts	Jan 2017	151,194	21,770	1,132	174,096
	Dec 2019	209,688	30,613	2,176	242,477
Share of hosts	Jan 2017	86.8%	12.5%	0.7%	
	Dec 2019	86.5%	12.6%	0.9%	
Active listings	Jan 2017	176,138	98,097	34,037	308,272
	Dec 2019	241,894	138,784	69,719	450,397
Share of active listings	Jan 2017	57.1%	31.8%	11.1%	
	Dec 2019	53.7%	30.8%	15.5%	
Avg. listings per host	Jan 2017	1.16	4.51	30.07	1,77
	Dec 2019	1.15	4.53	32.04	1,86

Notes:

a) The first two sets of rows refer to the actual number of active hosts at the beginning (January 2017) and at the end (December 2019) of the sample. The second two show the number of active Airbnb properties.

b) The average listings per host is the proportion of active properties to the number of active hosts.

Table 2.2a. Average entry rates for SSE, LSE and firms.

	National rates (%)	Provincial rates (%)
SSE [1-2 listings]	3.03	3.15
LSE [3-10 listings]	0.51	0.49
Firms [11+ listings]	0.06	0.05
Total	3.59	3.69

Notes:

a) Time span: monthly (January 2017 – December 2019).

b) Entry rates are calculated as the ratio of new entries in month t, then averaged over the sample time span.

c) National entry rates consider the Italian territory as a whole, while provincial entry rates average over the province in the dataset.

Table 2.2b. Average provincial entry rates by category.

	Total entries (%)	Brand new entries (%)	Entries (%) from			
			Gig	Mid	Large Firms	Other Provinces
SSE [1-2 listings]	3.15	2.76	–	0.16	0.01	0.23
LSE [3-10 listings]	0.49	0.12	0.30	–	0.03	0.06
Firms [11+ listings]	0.05	0.01	0.00	0.03	–	0.01
Total	3.69	2.89	0.30	0.19	0.04	0.32

Notes:

a) Time span: monthly (January 2017 – December 2019).

b) *Brand new entries* are hosts joining Airbnb for the first time (considering the entire Italian territory).

c) *Entries from Gig/Mid/Large Firms* are hosts upscaling or downscaling their status from other categories.

d) *Entries from Other Provinces* are hosts joining the market p having already been active in other provinces.

Table 2.2c. Average monthly revenues by category of hosts.

	AVG Monthly Revenues per Host	AVG Monthly Revenues per Property
SSE [1-2 Listings]	$ 501.24	$ 432.57
LSE [3-10 Listings]	$ 2,270.51	$ 582,80
SSE [1-3 Listings]	$ 571.79	$ 439.93
LSE [4-10 Listings]	$ 3,158.21	$ 639.85
SSE [1-4 Listings]	$ 624.27	$ 444.70
LSE [5-10 Listings]	$ 4,101.61	$ 694.35
Firms [11+ Listings]	$ 37,211.07	$ 954,82

Notes:

a) Mean values are displayed across multiple specifications of the threshold distinguishing gig entrepreneurs and middlemen (namely *k*).

Table 2.3a. Variables' descriptions.

	Variable	Description
Dependent Variables	Entries SSE [1-2] $e^2_{SSE,\,p,\,t}$	Net entries of SSE defined as hosts managing up to 2 listings simultaneously. The variable has been log transformed.
	Entries SSE [1-3] $e^3_{SSE,\,p,\,t}$	Net entries of SSE defined as hosts managing up to 3 listings simultaneously. The variable has been log transformed.
	Entries LSE [3-10] $e^2_{LSE,\,p,\,t}$	Net entries of LSE defined as hosts managing 3 to 10 listings simultaneously. The variable has been log transformed.
	Entries LSE [4-10] $e^3_{LSE,\,p,\,t}$	Net entries of LSE defined as hosts managing 4 to 10 listings simultaneously. The variable has been log transformed.
	$TRANS^n_{pt}$	Number of SSE transitioning to LSE according (i.e., increasing the properties managed from n to n+1). The variable has been log transformed.
	NEW^n_{kpt}	Brand new entries of entrepreneurs k=SSE,LSE according to threshold n. The variable has been log transformed.
Independent Variables And Control Variables	$MarketClimate^3_{pt}$	Perceived demand by prospective entrants for Airbnb accommodation calculated as the moving average of Reserved Nights in province p of the period from t-3 to t+3. The variable has been log transformed.
	$UnoccupiedDwellings_p$	Actual number of unoccupied dwellings in province p derived from the latest ISTAT census in 2011. The variable has been log transformed.
	$UnemplRate_{pt}$	Unemployment rate in province p at time t derived from ISTAT database.
	$HighRangeSpecialized_p$	Dummy variable equal to one if the proportion of four, five, and five luxury star hotels is higher than the sample median.
	$ConcentrationProp_{pt-1}$	Number of active Airbnb properties (considering all kind of hosts) in province p at time t-1 per surface unit.
	$AVGRent_{pt}$ [€/sqM Month]	Average monthly rent in province p at time t for Airbnb-type houses and residential units derived from the Osservatorio del Mercato Immobiliare (OMI). The variable has been log transformed.
	$Altitude_p$	Average weighted altitude of province p derived from ISTAT. The variable has been log transformed.
	$PercSeasideMunicipalities_p$	Proportion of seaside municipalities in province p derived from ISTAT
	$BedHotels_p$	Number of hotel beds in province p derived from ISTAT. The variable has been log transformed.

Table 2.3b. Descriptive Statistics.

	Variable	Mean	Std. Dev.	Min	Max
Dependent Variables	Entries SSE [1-2] $e^2_{SSE,\,p,\,t}$	62.35	92.19	0	1,493
	Entries SSE [1-3] $e^3_{SSE,\,p,\,t}$	62.31	92.35	0	1,486
	Entries LSE [3-10] $e^2_{LSE,\,p,\,t}$	10.50	16.13	0	157
	Entries LSE [4-10] $e^3_{LSE,\,p,\,t}$	6.35	10.22	0	103
Independent Variables And Control Variables	$MarketClimate^3_{pt}$	23,952	46,209	85	498,157
	$UnoccupiedDwellings_p$	65,777	43,159	10,407	254,098
	$UnemplRate_{pt}$	0.11	0.06	0.03	0.29
	$HighRangeSpecialized_p$	0.51	0.50	0	1
	$ConcentrationProp_{pt-1}$	1.60	2.26	0.05	15.98
	$AVGRent_{pt}$ [€/sqM Month]	3.49	1.72	0.24	9.08
	$Altitude_p$ [m]	343.18	216.19	4.28	1,157.62
	$PercSeasideMunicipalities_p$	0.21	0.26	0	1
	$BedHotels_p$	233,97	34,512	495	208,353

Table 2.4. Regression Output #1.

	SSE [1-2 listings]		SSE [1-3 listings]		LSE [3-10 listings]		LSE [4-10 listings]	
	RE	GMM-SYS	RE	GMM-SYS	RE	GMM-SYS	RE	GMM-SYS
	$Y = e^2_{SSE,\,p,\,t}$	$Y = e^2_{SSE,\,p,\,t}$	$Y = e^3_{SSE,\,p,\,t}$	$Y = e^3_{SSE,\,p,\,t}$	$Y = e^2_{LSE,\,p,\,t}$	$Y = e^2_{LSE,\,p,\,t}$	$Y = e^3_{LSE,\,p,\,t}$	$Y = e^3_{LSE,\,p,\,t}$
ln Y (p, t-1)	0.4409***	0.1755***	0.4356***	0.1571**	0.2351***	0.2274***	0.2465***	0.3888***
	(0.045)	(0.060)	(0.046)	(0.064)	(0.030)	(0.085)	(0.033)	(0.073)
ln $MarketClimate^3_{pt}$	0.3442***	0.5083***	0.3479***	0.5194***	0.4745***	0.4714***	0.4289***	0.3318***
	(0.029)	(0.042)	(0.029)	(0.044)	(0.026)	(0.058)	(0.028)	(0.049)
ln $UnoccupiedDwellings_p$	0.1061***	0.1570***	0.1069***	0.1569***	-0.0183	-0.0085	-0.0357	-0.0363
	(0.025)	(0.042)	(0.025)	(0.043)	(0.037)	(0.041)	(0.046)	(0.047)
$UnemplRate_{pt}$	1.1728***	1.6537***	1.1599***	1.6834***	2.7234***	2.5583***	2.3663***	1.5729***
	(0.294)	(0.556)	(0.303)	(0.578)	(0.393)	(0.593)	(0.432)	(0.464)
$HighRangeSpecialized_p$	0.0377	0.0610	0.0362	0.0591	0.0810**	0.0846*	0.0926**	0.0903**
	(0.025)	(0.044)	(0.025)	(0.045)	(0.039)	(0.048)	(0.042)	(0.037)
ln $AVGRent_{pt}$	-0.0092	-0.0195	-0.0088	-0.0205	-0.0416	-0.0529	-0.0058	-0.0164
	(0.031)	(0.056)	(0.030)	(0.056)	(0.048)	(0.054)	(0.058)	(0.063)
ln $Altitude_p$	0.0489***	0.0715***	0.0483***	0.0719***	0.0172	0.0220	0.0143	0.0224
	(0.014)	(0.023)	(0.013)	(0.023)	(0.023)	(0.024)	(0.026)	(0.029)
$PercSeasideMunicipalities_p$	0.1605***	0.2532***	0.1603***	0.2587***	-0.0302	0.0064	-0.0671	-0.0311
	(0.062)	(0.091)	(0.061)	(0.099)	(0.080)	(0.105)	(0.099)	(0.094)
ln $BedHotels_p$	0.0585***	0.0890***	0.0578***	0.0909***	0.0596***	0.0610**	0.0525**	0.0561**
	(0.016)	(0.026)	(0.016)	(0.028)	(0.021)	(0.025)	(0.024)	(0.026)
Constant	-3.3175***	-4.8823***	-3.3545***	-4.9632***	-3.7009***	-3.7952***	-3.3167***	-2.6945***
	(0.336)	(0.463)	(0.338)	(0.495)	(0.388)	(0.592)	(0.436)	(0.501)
N	3060	3060	3060	3060	3060	3060	3060	3060
Overall R2	0.9153		0.9150		0.8038		0.7400	
# Instruments		107		107		109		109
# Instruments / p		1,05		1,05		1,07		1,07
# Instruments / N		0,03		0,03		0,04		0,04
AR (1)		-5.22***		-4.99***		-5.57***		-6.80***
AR (2)		3.03***		2.81***		2.47**		3.88***
AR (3)		-2.85***		-2.93***		-1.21		-0.45
AR (4)		0.88		1.17		/		/
Hansen Test J (p-value)		100.38 (0.107)		100.8 (0.111)		95.38 (0.229)		87.48 0.438)

Notes:

a) Robust standard errors are in parenthesis. *** p<0.01; ** p<0.05; * p<0.10.

b) In GMM-SYS estimates, the instrument set is curtailed according to the Arellano-Bond AR (#) Test. $e^n_{SSE,pt-1}$ is instrumented with lags [t-4;t-5]. $e^n_{LSEpt-1}$ is instrumented with lags [t-3;t-4]. GMM models adopt two-step estimations and have been corrected with the Windmeijer (2005) covariance matrix for finite samples.

Table 2.5. Regression Output #2.

	SSE [1-2 listings]		SSE [1-3 listings]		LSE [3-10 listings]		LSE [4-10 listings]	
	RE	GMM-SYS	RE	GMM-SYS	RE	GMM-SYS	RE	GMM-SYS
	$Y = e^2_{SSE,p,t}$	$Y = e^2_{SSE,p,t}$	$Y = e^3_{SSE,p,t}$	$Y = e^3_{SSE,p,t}$	$Y = e^2_{LSE,p,t}$	$Y = e^2_{LSE,p,t}$	$Y = e^3_{LSE,p,t}$	$Y = e^3_{LSE,p,t}$
ln Y (p, t-1)	0.4204***	0.1631***	0.4165***	0.1510**	0.2193***	0.2239***	0.2155***	0.3677***
	(0.044)	(0.061)	(0.044)	(0.065)	(0.026)	(0.085)	(0.027)	(0.072)
$ConcentrationProp_{pt-1}$	0.0087	0.0019	0.0082	0.0096	0.0945***	0.1138***	0.1441***	0.1293***
	(0.023)	(0.042)	(0.023)	(0.043)	(0.033)	(0.035)	(0.035)	(0.037)
$ConcentrationProp_{pt-1}$^2	0.0015	0.0028	0.0015	0.0024	-0.0049**	-0.0061***	-0.0077***	-0.0072***
	(0.001)	(0.003)	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
ln $MarketClimate^3_{pt}$	0.3418***	0.4980***	0.3452***	0.5016***	0.4257***	0.4044***	0.3583***	0.2693***
	(0.031)	(0.047)	(0.032)	(0.047)	(0.031)	(0.060)	(0.032)	(0.043)
ln $UnoccupiedDwellings_p$	0.1174***	0.1631***	0.1177***	0.1670***	0.0105	0.0192	0.0069	-0.0003
	(0.024)	(0.044)	(0.024)	(0.046)	(0.036)	(0.042)	(0.043)	(0.040)
$UnemplRate_{pt}$	1.1709***	1.6911***	1.1561***	1.6208***	2.7008***	2.5328***	2.3461***	1.6785***
	(0.309)	(0.558)	(0.319)	(0.576)	(0.406)	(0.602)	(0.462)	(0.439)
$HighRangeSpecialized_p$	0.0332	0.0546	0.0317	0.0470	0.0821**	0.0800	0.0961**	0.1019**
	(0.026)	(0.043)	(0.026)	(0.046)	(0.039)	(0.050)	(0.041)	(0.040)
ln $AVGRent_{pt}$	-0.0253	-0.0428	-0.0243	-0.0443	-0.0662	-0.0758	-0.0411	-0.0412
	(0.031)	(0.057)	(0.030)	(0.052)	(0.044)	(0.049)	(0.048)	(0.043)
ln $Altitude_p$	0.0571***	0.0787***	0.0562***	0.0816***	0.0234	0.0237	0.0234	0.0268
	(0.013)	(0.022)	(0.012)	(0.022)	(0.021)	(0.023)	(0.023)	(0.023)
$PercSeasideMunicipalities_p$	0.1645**	0.2738**	0.1643**	0.2631**	-0.1589*	-0.1731	-0.2662**	-0.2290**
	(0.069)	(0.116)	(0.068)	(0.132)	(0.096)	(0.117)	(0.115)	(0.115)
ln $BedHotels_p$	0.0586***	0.0934***	0.0577***	0.0915***	0.0725***	0.0783***	0.0727***	0.0792***
	(0.015)	(0.026)	(0.015)	(0.026)	(0.021)	(0.027)	(0.022)	(0.024)
Constant	-3.3957***	-4.8880***	-3.4251***	-4.9419***	-3.7750***	-3.7535***	-3.4514***	-2.8552***
	(0.339)	(0.472)	(0.342)	(0.508)	(0.352)	(0.564)	(0.389)	(0.430)
N	3060	3060	3060	3060	3060	3060	3060	3060
Overall R2	0.9165		0.9160		0.8065		0.7465	
# Instruments		109		109		111		111
# Instruments / p		1,07		1,07		1,09		1,09
# Instruments / N		0,04		0,04		0,04		0,04
AR1 (p-value)		-5.16***		-4.96***		-5.57***		-6.76***
AR2 (p-value)		2.94***		2.76***		2.45**		3.79***
AR3 (p-value)		2.86***		-2.93***		-1.19		-0.46
AR4 (p-value)		0.85		1.16		/		/
Hansen Test J (p-value)		99.39 (0.120)		99.58 (0.118)		93.80 (0.265)		88.640.401)

Notes:

a) Robust standard errors are in parenthesis. *** p<0.01; ** p<0.05; * p<0.10.

b) In GMM-SYS estimates, the instrument set is curtailed according to the Arellano-Bond AR (#) Test. $e^n_{SSE,pt-1}$ is instrumented with lags [t-4;t-5]. $e^n_{LSEpt-1}$ is instrumented with lags [t-3;t-4]. GMM models adopt two-step estimations and have been corrected with the Windmeijer (2005) covariance matrix for finite samples.

Table 2.6. Carrying Capacity, and Maximum of Bell-Shaped Curve.

	LSE [3-10 listings]	LSE [4-10 listings]
Predicted Maximum ($-\gamma_{1,\mathrm{LSE}}/2*\gamma_{2,\mathrm{LSE}}$)	9.33	8.95
Std. Error Maximum	0.78	0.51
95% CI Lower Bound	7.80	7.95
95% CI Upper Bound	10.87	9.96
Percentage Observation after max	2.2%	2.3%

Notes:

a) Standard errors and confidence intervals are obtained through the Stata Command *nlcom*.

b) Results are based on the GMM-SYS estimate in Table 2.5. (columns 6 and 8).

Table 2.7. Short and Long Run Effects.

	SSE [1-2 listings]		SSE [1-3 listings]		LSE [3-10 listings]		LSE [4-10 listings]	
	SR	LRP	SR	LRP	SR	LRP	SR	LRP
ln $MarketClimate^3_{pt}$	0.4980***	0.5951***	0.5016***	0.5908***	0.4044***	0.5210***	0.2693***	0.4259***
	(0.047)	(0.028)	(0.047)	(0.026)	(0.060)	(0.035)	(0.043)	(0.042)
ln $UnoccDwell_p$	0.1631***	0.1949***	0.1670***	0.1967***	0.0192	0.0248	-0.0003	-0.000
	(0.044)	(0.052)	(0.046)	(0.054)	(0.042)	(0.055)	(0.040)	(0.063)
$UnemplRate_{pt}$	1.6911***	2.021***	1.6208***	1.909***	2.5328***	3.264***	1.6785***	2.655***
	(0.558)	(0.655)	(0.576)	(0.654)	(0.602)	(0.648)	(0.439)	(0.602)
$HighRangeSpec_p$	0.0546	0.065	0.0470	0.055	0.0800	0.1031*	0.1019**	0.1611***
	(0.043)	(0.051)	(0.046)	(0.055)	(0.050)	(0.062)	(0.040)	(0.061)
$ConcProp_{pt-1}$ $ConcProp_{pt-1}\text{^}2$	No significant effects on entries				Positive Linear effect, Negative Quadratic Effect. Concave relationship, Bell-Shaped. Maximum in 9.33-8.95			

Notes:

a) Standard errors and confidence intervals for the long run effects estimates are obtained though the Stata Command *nlcom*. *** p<0.01; ** p<0.05; * p<0.10. Results refer to the GMM-SYS models reported in Table 2.5.

b) $UnoccDwell_p$ = $UnoccupiedDwellings_p$; $HighRangeSpec_p$ = $HighRangeSpecialized_p$; $ConcProp_{pt-1}$ ($ConcProp_{pt-1}\text{^}2$) = $ConcentrationProp_{pt-1}$ ($ConcentrationProp_{pt-1}\text{^}2$).

c) SR = short-run effects (from Table 2.5., GMM-SYS estimates).

d) LRP = Long Run Propensity (derived from coefficients in Table 2.5., GMM-SYS estimates) = $\eta_{bk}/(1-\alpha_{1k})$, where η_{bk} is the estimated coefficient of variable b (b = $MarketClimate^3_{pt}$, $UnoccupiedDwellings_p$, $UnemplRate_{pt}$, $HighRangeSpecialized_p$) for entrant k (k = *SSE, LSE*) and α_{1k} is the coefficient of the lagged dependent variable for entrant k.

Table 2.8. Staged Large Scale entry and brand-new entry.

	$TRANS^2_{pt}$		$TRANS^3_{pt}$		NEW^2_{LSEpt}		NEW^3_{LSEpt}	
	RE	GMM-SYS	RE	GMM-SYS	RE	GMM-SYS	RE	GMM-SYS
ln $Y_{p,t-1}$	0.2158***	0.3083***	0.2221***	0.5855***	0.2211***	0.3054***	0.2100***	0.3186***
	(0.030)	(0.086)	(0.029)	(0.084)	(0.029)	(0.085)	(0.027)	(0.090)
$ConcentrationProp_{p,t-1}$	0.1126***	0.0904**	0.1553***	0.0774***	0.1195***	0.1025**	0.1309***	0.1139***
	(0.034)	(0.036)	(0.035)	0.030)	(0.044)	(0.043)	(0.041)	(0.040)
$ConcentrationProp^2_{p,t-1}$	-0.0054**	-0.0043*	-0.0080***	-0.0040**	-0.0066**	-0.0056**	-0.0071***	-0.0061**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
ln $MarketClimate^3_{p,t}$	0.3543***	0.3064***	0.2796***	0.1416***	0.2315***	0.1930***	0.1310***	0.0974***
	(0.031)	(0.051)	(0.031)	(0.036)	(0.029)	(0.036)	(0.025)	(0.024)
ln $UnoccupiedDwellings_p$	0.0290	0.0242	0.0322	0.0208	0.0115	0.0145	0.0073	-0.0051
	(0.036)	(0.039)	(0.039)	(0.028)	(0.042)	(0.046)	(0.040)	(0.033)
$UnemplRate_{p,t}$	2.2881***	1.7264***	2.0133***	0.8864**	1.9621***	1.6236***	1.4222***	1.0833***
	(0.416)	(0.465)	(0.432)	(0.421)	(0.354)	(0.447)	(0.315)	(0.333)
$HighRangeSpecialized_p$	0.1071***	0.1003**	0.1058***	0.0595**	0.1000***	0.0856**	0.0672**	0.0568*
	(0.039)	(0.041)	(0.038)	(0.025)	(0.037)	(0.040)	(0.032)	(0.032)
ln $AVGRent_{p,t}$	-0.0797*	-0.0757*	-0.0532	-0.0289	-0.0535	-0.0401	-0.0384	-0.0478
	(0.047)	(0.042)	(0.045)	(0.031)	(0.046)	(0.049)	(0.040)	(0.039)
ln $Altitude_p$	0.0300*	0.0274*	0.0179	0.0112	-0.0082	-0.0021	-0.0152	-0.0088
	(0.017)	(0.016)	(0.019)	(0.013)	(0.020)	(0.021)	(0.017)	(0.013)
$PercSeasideMunicipalities_p$	-0.1409	-0.0931	-0.2734**	-0.1154	-0.2832***	-0.1928*	-0.3670***	-0.2914**
	(0.094)	(0.092)	(0.107)	(0.077)	(0.109)	(0.117)	(0.108)	(0.118)
ln $BedHotels_p$	0.0718***	0.0674***	0.0669***	0.0384**	0.0682***	0.0646**	0.0602**	0.0602**
	(0.022)	(0.023)	(0.022)	(0.016)	(0.026)	(0.029)	(0.026)	(0.024)
Constant	-3.6277***	-3.1455***	-3.1644***	-1.7552***	Yes	Yes	Yes	Yes
	(0.378)	(0.499)	(0.378)	(0.375)	Yes	Yes	Yes	Yes
Month fe	Yes	Yes	Yes	Yes	-2.5232***	-2.3055***	-1.6631***	-1.2722***
Time Trend	Yes	Yes	Yes	Yes	(0.333)	(0.451)	(0.328)	(0.338)
N	3060	3060	3060	3060	3060	3060	3060	3060
Overall R2	0.777		0.713		0.630		0.496	
# Instruments		111		111		111		111
# Instruments / p		1,09		1,09		1,09		1,09
# Instruments / N		0,04		0,04		0,04		0,04
AR1 (p-value)		-6.12***		-7.07***		-6.15***		-5.73***
AR2 (p-value)		3.60***		4.60***		2.24**		1.72*
AR3 (p-value)		-1.22		-1.15		1.01		0.95
Hansen Test J (p-value)		86.10 (0.507)		84.26 (0.563)		88.74 (0.428)		84.59 (0.553)

Notes:

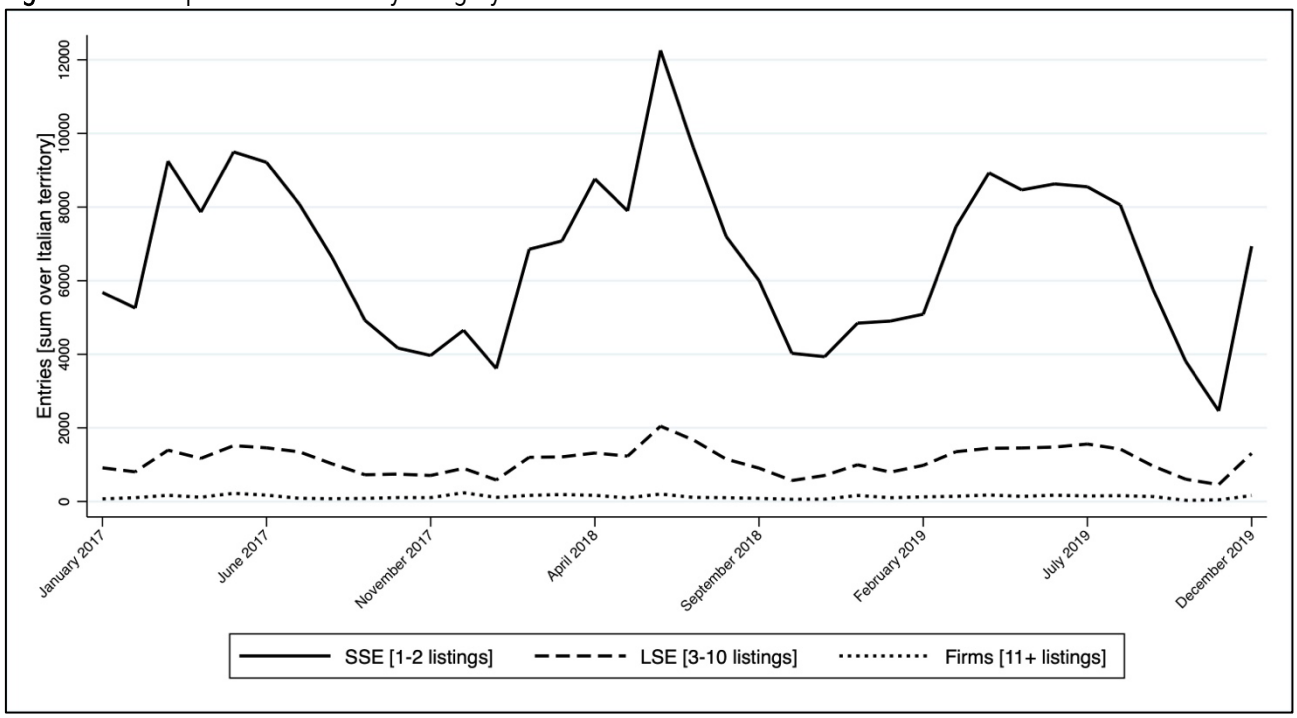
a) Robust standard errors are in parenthesis. *** p<0.01; ** p<0.05; * p<0.10.

b) In GMM-SYS estimates, the instrument set is curtailed according to the Arellano-Bond AR (#) Test. $e^n_{SSE,pt-1}$ is instrumented with lags [t-4;t-5]. $e^n_{LSEpt-1}$ is instrumented with lags [t-3;t-4]. GMM models adopt two-step estimations and have been corrected with the Windmeijer (2005) covariance matrix for finite samples.

c) $TRANS^n_{pt}$ = Number of hosts scaling from SSE to LSE according to threshold n; NEW^n_{SSEpt} = brand new LSE hosts (i.e., new active before on the platform).

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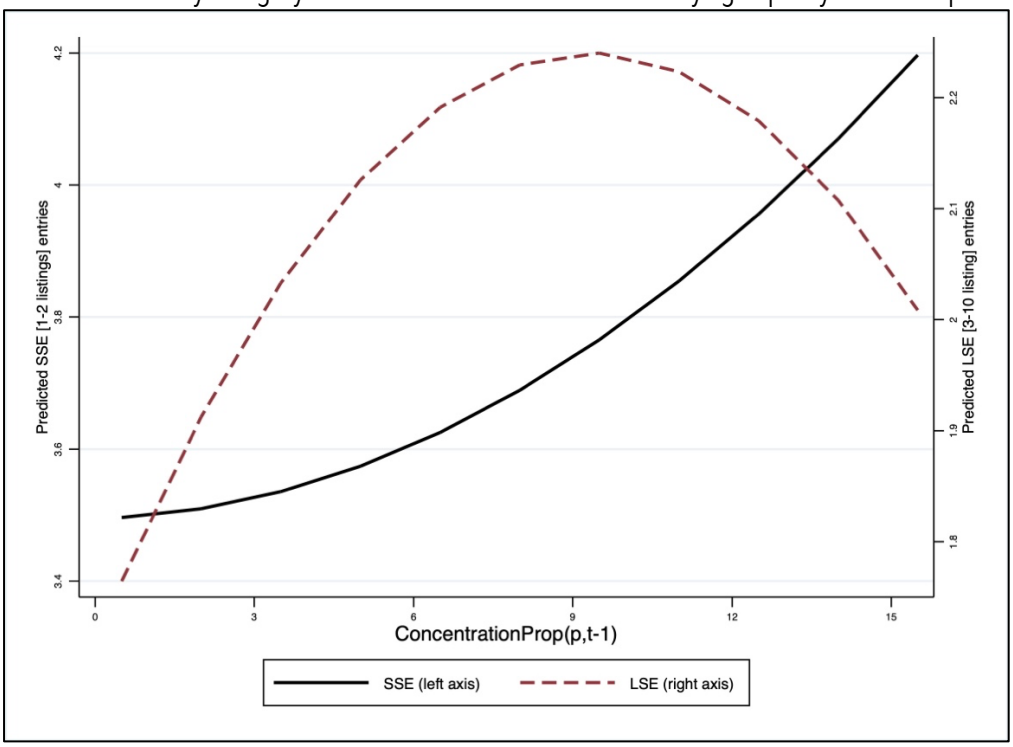
Figure 2.1. Entrepreneurs' entries by category.



Notes:

a) Time span: January 2017 – December 2019.
b) SSE own 1-2 listings, LSE own 3-10 listings, Firms own more than 10 properties.

Figure 2.2. Predicted Entries by category vs Local Market Concentration: Carrying Capacity & Bell-Shaped Curve.



Notes:

a) Marginal predictions are calculated according to different values of $ConcentrationProp_{pt-1}$, varying from very low, 0.5, to very high, 16, (see Table 2.3b.), keeping all other covariates at their mean value.
b) Predictions are estimated according to the GMM-SYS estimates shown in Table 5 (2nd and 6th columns).

c)

CHAPTER 3

The Pricing of European Airbnb Listings according to Demand Variations – A Difference-in-Differences Approach Employing the COVID-19 Pandemic and a Continuous Treatment

Abstract

The COVID-19 pandemic is a major exogenous shock impacting the global tourism industry over the last two years. Given its peculiarity, this study analyzes one of the most intriguing questions in the Airbnb literature – the pricing of Airbnb listings – while taking advantage of a difference-in-differences methodology, which largely draws on differences in country-level response policies to the pandemic. Relying on a dataset containing weekly information from 130,999 continuously active listings across 27 European countries from 2019 to 2020, this chapter firstly investigates the exogenous impact of response policies (proxied by the COVID-19 Stringency Index) on demand and, secondly, accounting for the endogeneity of demand for prices, analyzes pricing responses to demand variations. Results show that: i) increases in the COVID-19 Stringency Index cause significant declines of Airbnb demand; ii) increases in demand cause, on average, increases in Airbnb prices; and iii) the pricing strategy differs between commercial and private hosts.

Keywords

Airbnb, COVID-19, Difference-in-Differences (DID), Pricing, Two-Stage Least Squares (2SLS).

Credits & Acknowledgments

This chapter is extrapolated from a paper jointly written with Prof. Ulrich Gunter (Modul University Vienna) and Prof. Bozana Zekan (Modul University Vienna).

The author(s) thanks to FULL – The Future Urban Legacy Lab for its financial support. I am grateful to the attendees of the 8th IATE Conference in Perpignan for their comments and suggestions and to the Scientific Committee of the 8th IATE Conference for awarding the corresponding paper with the Best Paper Award.

3.1. Introduction

This chapter, drawing on the wide and unexpected shock caused by Covid-19 pandemic, answers one of the most researched questions within the Airbnb, and generally tourism-related, domain, by assessing how service providers price their amenities (Cai et al., 2019; Hernandez et al., 2021) on the basis of variations of the local demand. Compared to the previous contributions, who have mainly assessed Airbnb pricing by the means of hedonic-style models (i.e., assessing the impact of visible characteristics such as dimension, location, etc., on prices, e.g., Sainaghi et al., 2021), this study provides a novel point of view, including a market-based perspective, thus estimating the price to demand elasticity. Furthermore, in line with the spirit of the previous chapter (i.e., Chapter 2), which has shown that significant differences are likely to exists across different types of service providers (i.e., small scale vs large scale hosts), this study declines the pricing response to demand also according to the typology of the host.

On the basis of these premises, this study provides a novel contribution to the literature as long as the estimation of price to demand elasticity is identified according to a continuous treatment approach (Callaway et al., 2021). Indeed, grounding on the shock caused by Covid-19 pandemic, and the respective strategies adopted by governments to face the widespread of infections, this study provides a two-stage estimation of prices, where local demand is instrumented in the first stage exploiting cross-country variations of Covid-19 response strategies. In order to do so, this research uses (being among the firsts to do so, at the best of the author's knowledge) the contribution of Hale et al. (2021), who developed the Covid-19 Stringency Index, to exogenously determine the local demand faced by each host and, consequently, estimating the corresponding pricing response.

The rest of the chapter is organized as follows. Section 3.2. briefly revises the major contributions to the literature of Covid-19 pandemic related to tourism, Airbnb's pricing and respective continuous treatment applications, Section 3.3. introduces presents the data and all the variables employed in the models, Section 3.4. describes the empirical methodologies, Section 1.5. illustrates the results while Section 1.6. provides a discussion of the results and a sub-section on the directions for future improvements of the research as well as the limitations of this research endeavor.

3.2. Related Literature

Grounding the main methodological features on the shock caused by Covid-19 pandemic, this section provides an exhaustive review of the two core streams tackled by this study: Airbnb pricing on the one side, and causal inference methods with continuous treatment on the other, as well as a brief review on the literature examining the impact of Covid.

3.2.1. Airbnb Pricing studies

The determinants of Airbnb pricing has always been a widely debated topic in literature. Cai et al. (2019) state that this topic is in "its infancy", however, three years later and with rapidly growing interest among researchers, this claim no longer holds. To support this, Hernández et al. (2021) examine 18 studies published between 2016 and 2020 to

summarize price determinant estimations for Airbnb listings. Five groups of price determinants are identified by these authors in the literature: structural attributes (e.g., property characteristics and services), host attributes (both personal and relational), management attributes (e.g., specific rental rules), reputation attributes (e.g., reviews and ratings), and location attributes (e.g., spatial and environmental factors). Such classifications are consistent across the literature (e.g., Arvanitidis et al., 2020; Cai et al., 2019). Simply put, prices are driven by "the physical characteristics - the what; the factors which impact user perception - the why; and, the location - the where" (Perez-Sanchez et al., 2018, p. 26). Several important take-aways from past studies on Airbnb pricing are highlighted in the following, which explore various explanatory variables, pricing differences between private (also referred to as non-professional or casual) and commercial (i.e., professional) hosts, and price discrimination.

Cai et al. (2019) examine the impacts of five categories of explanatory variables in their investigation of price determinants of Airbnb listings in Hong Kong by employing hedonic price regression. Among other results, they find that the hosts' listings count has a negative effect and that the room type exerts an exceptionally high impact on the price. A comparison of different methodological approaches (OLS regression, random forest, and decision tree) is performed by Chattopadhyay and Mitra (2019) in their investigation of Airbnb price determinants in eleven US cities. Besides highlighting city-specific variable importance, the authors also estimate a composite score of variable importance. Furthermore, general product features, reviews of quantity and quality, as well as amenities and services are identified as important Airbnb price determinants in Toronto (Chattopadhyay & Mitra, 2020), whereas more reviews are linked with lower prices according to the hedonic pricing model applied to listings across five major urban destinations in Canada (Gibbs, Guttentag, Gretzel, Morton, & Goodwill, 2018). Another interesting finding is that the subjective and objective internal attributes in title descriptions play a differing role in determining the Airbnb prices in Swiss rural and urban locations (Falk et al., 2019).

Arvanitidis et al. (2020) contribute with an in-depth exploration of Airbnb listing prices between "casual" (i.e., with one or two listings) and professional (i.e., with more than two listings) hosts in Athens by applying hedonic price modeling and a Blinder-Oaxaca decomposition, thereby providing evidence of a statistically significant difference in pricing. Spatial price mimicking on Airbnb is the focus of the study by Boto-García et al. (2021), who suggest that price mimicking is higher among non-professional (i.e., single-property) hosts in comparison to professional hosts in Madrid. The latter two studies demonstrate that there is no universal consensus in the Airbnb literature as to the listing count threshold defining an Airbnb host as 'professional' or not.

In terms of price discrimination, Aznar et al. (2018) conclude that Airbnb hosts in Barcelona discriminate prices according to seasonality, but generally not in terms of day of the week. Although host attributes are important price determinants (Wang & Nicolau, 2017) and act as trust indicators (Fleischer et al., 2022), the recent contribution by Barnes (2021) warns about the overvaluation of perceived facial trustworthiness in Airbnb host images, especially in combination with reputational measures.

Regarding locational factors, accessibility to certain amenities, walkability, noise, the ethnicity of residents, as well as spatial spillover effects are confirmed to have a statistically significant impact on Airbnb pricing in Málaga (Chica-Olmo et al., 2020). Similarly, in their study on determinants of Airbnb prices in ten major EU cities, Gyódi and Nawaro (2021) identify attributes related to size, quality, and location as significant, and conclude that prices are spatially dependent. In addition, listing characteristics, the number of points of interests within an optimal radius (= 650m for Tallinn, as estimated via a simulation study), and prices of other Airbnb listings and hotels within the same radius are found to positively impact prices of Tallinn's Airbnb listings (Önder et al., 2019).

Also applying a hedonic pricing model, Tong and Gunter (2020) determine that overall rating and characteristics indicative of the size of the listing have the strongest positive influence, whereas the number of reviews and distance from the city center exert the strongest negative influence on Airbnb prices in Barcelona, Madrid, and Seville. Recognizing the relevance of spatial factors in a study of listings in Los Angeles and New York, Hong and Yoo (2020) propose a multiscale geographically weighted regression (MGWR) approach for analyzing spatial variance of Airbnb pricing determinants. Despite this clear academic interest in Airbnb prices, the literature also notes differences between price and revenue determinants (Sainaghi et al., 2021). The determinants of demand, when measured through occupancy rates, for instance, reveal that "it is not all about price, indeed" (Leoni et al., 2020, p. 1707).

3.2.2. Covid-19 pandemic and Tourism/Airbnb

Over the past two years, the COVID-19 pandemic disrupted the global tourism and hospitality industry like no other crisis experienced in the past. Given that the sharing economy is often described as "a disruptive phenomenon" (Hossain, 2021), it comes natural that many researchers are nowadays interested in exploring the impacts of the pandemic on the sharing economy as a whole and on Airbnb in particular, along with the recovery prospects. On that note, Dolnicar and Zare (2020) are likely the first to put forward the notion of two simultaneous disruptors (i.e., COVID-19 and Airbnb).

An important lesson learned so far is that COVID-19 exposed the vulnerability of the sharing economy. Chen et al. (2022) conclude this by assessing the income loss of Airbnb hosts at both spatial and temporal scales in Sydney with a comprehensive income accounting framework. Hossain (2021) concentrates on survivability and therefore examines the impact of the pandemic on various sharing economy activities. Similarly, the question of whether COVID-19 will terminate or rather accelerate the growth of peer-to-peer accommodation (P2PA) is raised in the study by Zhang et al. (2021), who investigate the responses of hosts to the pandemic in China. They ultimately find that COVID-19 is "an accelerator that preserves the "real" P2PA and eliminates hosts who only pursue profit opportunities" (Zhang et al., 2021, p. 8). P2PAs are also of interest to Farmaki et al. (2020), who identify existing variance in host perceptions and responses to the pandemic. Regarding organizational response strategies to the pandemic in the sharing economy, Mont et al. (2021) compare 30 platforms on shared mobility, space, and goods, and propose cross-platform learning to optimize both crisis response and preparedness.

Further insights on the impact of COVID-19 on vacation rentals in twelve mega cities across the world come from Liang et al. (2021), which can be used as a reference for other cities. One of the merits of this study is a methodological assessment framework for monitoring the hospitality sector. Exploring causal factors on performance, Gerwe (2021) outlines the underlying reasons for disruption (i.e., the weak points) of the accommodation sharing sector, along with the prospects for recovery as the pandemic may push the "reset button". Acknowledging the importance of destination-specific response strategies, Jang and Kim (2022) propose remedying Airbnb COVID-19 disruption through local resources: tourism clusters and community resilience.

There is also evidence that the changes in demand during COVID-19 differ by accommodation type. To this end, Bresciani et al. (2021) investigate the impact of the pandemic on different accommodation types and conclude that full flats are preferred over shared flats on Airbnb and over hotel rooms, in line with travelers' needs for physical distance. Perceived risks of using Airbnb were rated higher during the pandemic than previously (Lee & Deale, 2021). Moreover, based on the spatial and experimental analysis of P2PA consumption during COVID-19, it is found that (1) revenue losses differ across destinations (i.e., urban and rural areas) and destination attributes (i.e., tourism clusters, airport distance, and food safety violation) and (2) business tourists who perceive the pandemic as a low threat are more willing to use Airbnb listings than leisure tourists (Jang et al., 2021).

As the latter finding holds irrespective of the destination type (i.e., rural or urban), the authors suggest a number of managerial implications for both rural and urban Airbnb hosts. Unsurprisingly, short-term rentals in low-density areas are described as a suitable option for travelers (Zoğal et al., 2020), given the difficulty of social distancing in urban destinations (Jang et al., 2021). Such conclusions corroborate the pandemic-induced dynamic changes in overall travel demand and consumer preferences noted by Kim et al. (2021) and suggest revisiting the motivating factors and market segments for Airbnb that were proposed by Guttentag et al. (2018). Moreover, social interaction was not found significant with regard to perceived enjoyment and repurchase intention of Airbnb experiences (So et al., 2021), which is also likely to be reconfirmed in the aftermath of the pandemic.

3.2.3. Causal Inference approaches within Airbnb domain

The final reflection, which, for the purpose of the study, bridges the presented streams of literature, concerns the Airbnb studies employing a two-stage least squares (2SLS) estimation in general, and a difference-in-differences (DID) approach in particular, since causal inference is at the core of the empirical analysis. For example, Benítez-Aurioles (2018) opts for a 2SLS regression in estimating the elasticity of Airbnb demand to price and distance in Barcelona and Madrid, finding similarities between the cities with respect to price elasticity of demand. In their exploration of the determinants of Airbnb location and its spatial distribution, Eugenio-Martin et al. (2019) employ bivariate spatial correlation and spatial econometric techniques, thereby identifying price as the main determinant of Airbnb location. Among other analytical techniques, the 2SLS regression is used in the empirical investigation of the importance of tourism clusters in P2PA in the study by Lee et al. (2020).

Contributions employing the DID estimation technique within this thematical domain are also growing in numbers, especially over the past few years. Of interest to the present research is the study by Benítez-Aurioles (2019), who uses an extended DID formulation for assessing the impact of sociopolitical instability on Barcelona's P2P tourist accommodation market. Similarly, the DID technique is adopted to understand the impact of terrorist attacks on the P2PA market in Paris, which, predictably, has a significant negative effect on both market demand and rental performance (Chen et al., 2021). Yeon et al. (2020) apply both DID and a triple difference (DDD) approach in examining the impact of short-term rental regulation on P2PA performance, demonstrating a substantial difference between the pre- and post-regulation. Such types of modeling are also used in examining the impacts of: (1) Airbnb on hotel performance and employment (e.g., Mhlanga, 2019, 2020, 2021), (2) consumer animosity on demand for sharing-based accommodations (e.g., Li et al., 2021), and (3) the offshore wind farm on the vacation rental market (e.g., Carr-Harris & Lang, 2019). Despite these diverse areas of application, to the best of authors' knowledge, no study to date has applied DID to the pandemic context. A further novelty of the present study is the application of DID with a continuous treatment, which has only very recently been added to the econometrician's toolbox (Callaway et al., 2021).

3.3. Data and Variables Description

This section presents the data employed in the econometric analyses, providing descriptions of the data sources and the operationalization of the variables, complemented by the respective descriptive statistics.

3.3.1. Data Sources

This study takes advantage of the data provided by AirDNA, a leading provider of data on short-term rentals. Our panel dataset covers the period from January 1st, 2019, to December 31st, 2020, and contains information on prices, demand (i.e., the number of reserved nights), activity status, and other listing-level structural characteristics for continuously active[55] properties from 27 European countries, whose list is reported in Table 3.1. From the original dataset with a listing-daily scale, all variables were aggregated to a weekly basis in order to deal with the large dimensionality of a listing-level panel dataset covering properties from 27 European countries over two years. Given the nature of our analysis, data has been restricted to include only those listing-week observations that received at least one reservation during the observation period (as often done in literature, e.g., Gunter & Önder, 2018; Gunter, 2018; Ert & Fleischer, 2019). The final operationalization of the variables, which uses backward and forward time lags of demand variables (explained in the following sections), results in a final panel dataset containing 2,205,347 listing-week data points. Table 3.1. and Figure 3.1. offer an overview of the distribution of listings and corresponding reservations and revenues by country, showing a clear dominance by the larger touristic markets such as France, Italy, or Spain, both in terms of property numbers and reservations/revenues.

[55] A property *i* is defined active at time *t* if the sum of *Reserved Nights* plus *Available Nights* during *t* (where *t* is a week in this paper) is positive.

[Insert Table 3.1. here.]

[Insert Figure 3.1. here.]

The dataset from AirDNA is complemented by other data sources. From Eurostat[56] and from the European Central Bank datasets[57], macroeconomic variables such as the country-level real gross domestic product and consumer price index (with the base year 2010), both expressed in USD, have been retrieved. From Our World in Data[58], the COVID-19 Stringency Index, measuring the intensity of governmental restrictions in response to the COVID-19 pandemic at the country level (Hale et al., 2021) and is employed as an instrumental variable in the following econometric analyses, has been gathered.

3.3.2. Variables Operationalization

Dependent Variable: Average Weekly Price. The aim of this study is to analyze whether variations in local demand determine variations of listing-level posted-prices. To this end, the dependent variable in the analysis is the average price (net of any additional fees, such as cleaning fees or extra people fees), measured in USD, that a property *i* proposes in week *t* (*t* varying from 0 = week one of 2019, to 104 = week 52 of 2020). Departing from previous literature on pricing in the tourism sharing economy, which has mainly focused on the Average Daily Rate (ADR) as approximation of prices (Sainaghi et al., 2021), this analysis employs the real prices posted on the platform as the dependent variable. This approach yields several advantages according to the purpose of this research to the extent that it aims at measuring the causal impact of local demand variations on hosts' pricing *decisions*. Indeed, the ADR represents the price that is effectively realized (i.e., supply and demand decisions met) and not the price actually offered to customers (Canina & Enz, 2006). Assuming that these two metrics are equivalent would be equal to assume that supply and demand are always in equilibrium, which is considered unlikely during the pandemic. Consistently, the usage of average weekly price fits better with the goal of understanding hosts' pricing decisions. In the econometric models, the variable has been log transformed.

Explanatory (Endogenous) Variable: Local Airbnb Demand. The definition of local demand in the Airbnb context is not obvious, as multiple determinants make the concept complex to measure; these include the dimension of the relevant market which the listing addresses (in our case the spatial boundaries determining the competitors of a property), and the timing of demand. To deal with this complexity, this study proposes the following definition in Eq. 3.1:

$$\text{Local Airbnb Demand}_{i,r,t,f} = \sum_{t=\tau-f}^{t=\tau+f} \text{Reserved Nights}_{i,r,\tau}/(2f+1) \qquad \text{(Eq. 3.1.)}$$

[56] Data can be accessed through the following link: https://ec.europa.eu/eurostat/data/database.
[57] Data can be accessed through the following link: https://www.ecb.europa.eu/stats/html/index.en.html.
[58] Data can be accessed through the following link: https://ourworldindata.org/covid-stringency-index.

Local demand is thus defined as a moving average from *f* weeks in the past to *f* weeks ahead of *t* of the number of reserved nights of listing *i* plus the number of reserved nights of other listings in the neighboring vicinity, specified as those Airbnb listings located within radius *r* of listing *i*. On the basis of contributions investigating the size of the Airbnb property-level relevant market (see, e.g., Önder et al., 2019, who find a radius of 650m to be optimal for studying cross-price influences in the city of Tallin), the model specifications are tested over four different *r* values ranging from 250m to 1,000m in 250-meter increments.

The length of the averaging period *f* is specified as three, thus conservatively assuming that demand over the coming three weeks is known in week *t* and that hosts decide on their prices in week *t* based on these future expectations as well as past experience. As often assumed in the Airbnb literature (see, e.g., Gunter et al., 2020), this implies a market structure of monopolistic competition characterized by heterogeneous Airbnb offerings allowing some leeway for hosts to set their own prices (Chamberlin, 1933; Dixit & Stiglitz, 1977; Robinson, 1933). Moreover, the application of a moving average allows the explanatory variable to smooth out potential seasonal patterns in the data. In line with the dependent variable, the explanatory variable has also been log transformed to enable the respective coefficient estimates in the econometric models to be interpreted as elasticities.

Instrumental Variable: Covid-19 Stringency Index. To deal with the endogeneity of the variables employed in the econometric models (i.e., using demand to explain prices), the COVID-19 Stringency Index has been identified as a proper instrumental variable of Local Airbnb Demand. This metric, developed by Hale et al. (2021)[59], is a composite daily measure based on nine policy response indicators (namely: school closures, workplace closures, cancellation of public events, restrictions on gathering sizes, public transport closures, stay-at-home policies, restrictions on within country movements, restrictions on international travel) adopted by countries to deal with the COVID-19 pandemic. The metric is computed per country and rescaled as an indicator varying between 0 (no restrictions at all) and 100 (the most restrictions). In line with the temporal dimension of the panel data, COVID-19 Stringency Index data were aggregated at a weekly level by taking the mean value. Furthermore, in order to correctly match the instrumental variable with the instrumented Local Airbnb Demand, the COVID-19 Stringency Index is included in the model as reported in Eq. 3.2.:

$$\text{COVID} - 19\ \text{Stringency Index}_{\text{i,g,t}} = \sum_{\text{t}=\tau-\text{f}}^{\text{t}=\tau} \text{Weekly COVID} - 19\ \text{Stringency Index}_{\text{i,g,}\tau}/(\text{f}+1)$$

(Eq. 3.2.)

where *g* is the country containing listing *i* and *f* is the window length of the moving average filter. In line with the definition of Local Airbnb Demand, *f* is set to three and thus reports the average restriction level over the preceding three weeks. Given the definition of the COVID-19 Stringency Index variable, it is possible to conservatively assume that the metric is

[59] The computational procedure of this indicator is available on the corresponding journal article from Hale et al. (2021) available on Nature Human Behavior (see the list of references). On the other hand, data on the indicator are available on the web-portal Our World In Data (see section 3.3.1.).

highly correlated with the instrumented Local Airbnb Demand, yet is exogenous in our estimation as direct correlation with Average Weekly Price is highly unlikely. In other words, to the extent that the Covid-19 pandemic resulted in an exogenous shock, and the corresponding policy restrictions exogenously determined losses in demand, it is likely to assume (in a conservative manner) that this instrumental variable is not *directly* correlated with the dependent variable (Average Weekly Price). Still, it is likely that by influencing demand, Covid-19 Stringency Index may be correlated with prices too, although this correlation is not direct, but actually, mediated by demand expectations. The instrument validity (i.e., significant correlation with the endogenous Local Airbnb Demand) is discussed in Section 3.5. by the means of proper statistical tests such as the Kleibergen-Paap weak instrument statistic (Kleibergen & Paap, 2006).

[Insert Figure 3.2. here.]

Figure 3.2. reports the evolution of the average values of the COVID-19 Stringency Index and Local Airbnb Demand over time. At a glance, Figure 3.2. shows a strongly negative correlation between the instrumented and the instrumental variable. Indeed, as the COVID-19 Stringency Index rose following the pandemic outbreak, we note a strong decrease in Local Airbnb Demand. When restrictions declined in summer 2020, local demand grew, before reservations in the Airbnb market fell again with tightening restrictions from October to December 2020.

(Additional) Control Variables. Other than providing a two-way fixed effects estimates only (as reported in section 3.4.), robustness testes employing various control variables at different geographical levels are incorporated into the models to account for factors affecting both demand and prices.

Firstly, given the spatial nature of the data and the likelihood of spatial autocorrelation (Tobler, 1970), the average prices (Average Market Price) and the number of competing Airbnb listings (Number of Competitors) within the relevant market (i.e., the corresponding radius r as chosen for the definition of demand, tested across different model specifications) have been included in the set of control variables.

Secondly, additional controls for country-level macroeconomic factors have been tested, i.e., factors that jointly affect either pricing decisions or short-term rental demand for all Airbnb listings within country g in week t (Gunter et al., 2020). To this end, the annual country-level real gross domestic product (RGDP) and the consumer price index (CPI), both in USD and referring to the same base year, 2010 have been additionally included as control variables[60].

Finally, as long as time-(in)variant host and property characteristics can supposedly impact both prices and demand, further host-listing level controls have been included. Specifically, the following variables have been included among the controls: i) the number of beds (Beds) since larger sized accommodations normally attract higher prices (Sainaghi et al., 2021); ii) the number of photos (Photos) proxying the way hosts market their property on the platform (Gunter & Önder, 2018); iii) the managerial competencies of the host, approximated by the number of properties they manage within the sample (Host's Properties; Dogru et al., 2020; Li et al., 2016; Xie et al., 2021); iv) a dummy variable indicating whether

[60] These macroeconomic control variables were employed while retaining their original quarterly (*RGDP*) and monthly (*CPI*) frequencies.

the listing is active on multiple platforms such as VRBO (Multiplatform; =1, =0 otherwise); v) the duration of host's subscription to the Airbnb platform in days (Experience), which – to the best of author's knowledge – has not been investigated in the literature so far; vi) a dummy variable (Cancellation Policy) indicating the host's imposition of a strict or moderate cancellation policy (=1) versus a flexible one (= 0; Tong & Gunter, 2020); vii) a dummy variable (Instantbook) for the possibility of instant booking (=1, =0 otherwise; Mayya et al., 2020); and, finally viii) a dummy variables (MidLong Rent) for properties only available for medium- to long-term rentals (i.e., more than 30 days =1, =0 otherwise; Deboosere et al., 2019).

In order to deal with the seasonal patterns within data, the time-invariant controls are interacted with seasonal dummy variables in the following two-way fixed-effects models (otherwise their effects is already captured by the individual fixed effect). Here, the seasons of the year correspond to the astronomical seasons of Europe. All continuous control variables are log transformed in the econometric models. Table 3.2. provides descriptive statistics of all variables employed in the econometric models.

[Insert Table 3.2. here.]

3.3.3. Additional Specifications and Sample Splits

Following the main estimations, an additional analysis, disentangling differentials in the results according to the typology of the host, is provided. In this vein, the variable *Host Type* has been generated to distinguish categories of hosts according to the number of properties managed. The variable takes the value *Private Host* (i.e., small scale host) if the number of properties managed by the host is less than or equal to two and the value of *Commercial Host* (i.e., large scale host) if the number of properties managed is three or more. Although there is not a common threshold in the literature for distinguishing hosts as either private or commercial, a value of three falls within the range of values commonly used (Deboosere et al., 2019; Dogru et al., 2020; Gunter & Önder, 2018) and therefore reflects the typical Airbnb host typologies found in the literature. In total, 26% of listings within the dataset are managed by commercial hosts and 74% by private hosts.

3.4. Empirical Methodology

Given the panel structure of the data, it is necessary to employ adequate panel-estimation techniques (see, e.g., Wooldridge, 2010, for an overview). As the analyses are confronted with i) an endogenous explanatory variable of Average Weekly Price ($AWP_{i,t}$), namely Local Airbnb Demand ($LAD_{i,t,r}$), ii) the outbreak of the COVID-19 pandemic ($POST_t = 1$ if $t \geq 63$, i.e., the 11th week of 2020, =0 otherwise), and iii) the COVID-19 Stringency Index ($CSI_{g,t}$) as a country-level continuous treatment (Callaway et al., 2021), a two-stage least squares (2SLS) approach — specifically, a two-way fixed-effects (TWFE) difference-in-differences (DID) design with continuous group level (i.e., country) treatment — is applied (Callaway et al., 2021; Kandrac, 2021; Wooldridge, 2010). As opposed to the traditional DID design, in this empirical

setting all individuals are treated at the same time (by the outbreak of the COVID-19 pandemic) yet with differing treatment intensities (according to the COVID-19 Stringency Index).

The econometric model for listing *i* in week *t* located in country *g* and dependent on radius *r* reads as follows (Kandrac, 2021):

$$\ln \mathrm{LAD}_{i,t,r} = \beta \cdot \ln \mathrm{CSI}_{t,g} \cdot \mathrm{POST}_t + \delta \cdot \mathrm{X}_{i,t,g,r} + \theta_t + \eta_i + u_{i,t}$$

(Eq. 3.3.)

$$\ln \mathrm{AWP}_{i,t} = \alpha \cdot \ln \widehat{\mathrm{LAD}}_{\imath,t,r} + \gamma \cdot \mathrm{X}_{i,t,g,r} + \theta_t + \eta_i + u_{i,t}$$

(Eq. 3.4.)

Eq. 3.3. represents the first-stage regression of the 2SLS estimation, whereas Eq. 3.4. represents its second-stage regression and includes the fitted values of Local Airbnb Demand obtained from the first-stage regression. $X_{i,t,g,r}$ denotes a vector of spatial, macroeconomic, and listing-level control variables (see Section 3.3.2. for more details), as well as a constant term. θ_t represents the time fixed effect, η_i the individual fixed effect, and $u_{i,t}$ the idiosyncratic error term.

Two different specifications of the econometric models, one including the time-invariant control variables (interacted with seasonal dummies to deal with the individual fixed effects) and one omitting these variables, are proposed as main estimation results. The majority of the models presented are estimated without including these controls because of the associated computational burden, and because it is possible to conservatively assume that their effect is already included in the individual fixed effect as long as their seasonal variation does not significantly affect the elasticity of price to demand.

As reported in Section 3.3.2., all variables except for the dummy variables are transformed to natural logarithms to make effect sizes interpretable as scale-free elasticities[61]. As can be seen from Figure 3.3., the necessary parallel trends assumption (Callaway et al., 2021) can be considered fulfilled: the outbreak of the COVID-19 pandemic represented a natural (quasi) experiment, an exogenous event that could not be anticipated and that had a common impact across European countries, which, however, has been treated at different and varying intensities on the basis of governments' responses. The employed standard errors are robust and clustered at the listing level. In addition to the 2SLS results, the research also presents cluster-robust OLS results to showcase the misjudgment of effect sizes if one fails to treat Local Airbnb Demand as endogenous (see Section 3.5.2. for the main estimation results). All estimations are performed in Stata Version 17, while employing the '*ivreghdfe*' wrapper (Correia, 2018) for the 2SLS estimations and the '*reghdfe*' wrapper (Correia, 2015) for the OLS estimations in order to deal with the large dimensionality of the fixed effects[62].

[Insert Figure 3.3. here.]

[61] To be precise, the transformation *ln(1+x)* was performed per each non-binary variables *x.*

[62] *reghdfe* indeed stands for "REGression with High Dimensional Fixed Effects" (Correia, 2018), which is particularly useful when dealing with large databases like the one used in this chapter.

In the following, the econometric model given by Eqs. 3.3. and 3.4. is applied to various sub-samples of the panel dataset depending on the variable Host Type, which complement the analysis (see Section 3.5.3.). Finally, to confirm the validity of the results regardless the operationalization of the main variables, three different robustness checks are tested (see Section 3.5.4.). First, in the DID setting, multiple definitions of the timing of the pandemic outbreak are used (see the variable $POST_t$). Second, since no clear definitions exists in the extant literature for either the moving average period applied to demand or for the threshold distinguishing private (i.e., small scale) and commercial (i.e., large scale) hosts, further robustness checks vary the operationalization of these two variables.

3.5. Results

3.5.1. First Stage Results: The Impact of Restrictions on Airbnb Demand

Given the mounting interest in the impact of COVID-19 response policies, Table 3.3. shows the estimates of the first stage equation, estimating Local Airbnb Demand by means of the COVID-19 Stringency Index (i.e., the interaction term between the continuous treatment COVID-19 Stringency Index and the $POST_t$ dummy equals to one if $t \geq 63$). Two models are proposed: Model 1 (in Table 3.3A.) includes all time-invariant control variables (interacted with the season-of-year categorical variable) and tests Eq. 3.3. over one specification (namely: Spec. 2: r=500m) ; Model 2 (in Table 3.3B.) does not consider time-invariant characteristics (postulating that their effect is already accounted by the individual fixed effects and does not significantly vary over seasons), but tests Eq. 3.3. over four specifications (namely: Spec. 1: r=250m, Spec. 2: r=500m, Spec. 3: r=750m, Spec. 4: r=1000m). Given that both models provide comparable results as well as similar goodness of fit measures (i.e., the Adjusted R2 is comparable), thereby confirming the assumption that time-invariant property-level characteristics are effectively captured by the individual fixed effects, the subsequent discussion focuses on Model 2, which analyzes the impact of restrictions on Local Airbnb Demand over different specifications of r.

[Insert Table 3.3. here.]

Specifications 1 to 4 of Model 2 (Table 3.3B.) show that, coeteris paribus, a one percent increase in the COVID-19 Stringency Index after the pandemic outbreak is associated with a decrease in Local Airbnb Demand varying from a -0.133 to -0.155 percent (all coefficients significant at 99.9% confidence level), with effects becoming larger as the radius defining Local Airbnb Demand increases. Interestingly, the performance of the models according either to the R2 measures or the information criteria (Akaike's Information Criterion, AIC; and Bayesian Information Criterion, BIC; Lütkepohl, 2005) improve as the radius increases, confirming better model performance as the dimension of the relevant market gets closer to the group-treatment dimension. The control variables included in the models show the ex-ante expected signs: increases in average prices of neighboring listings showing a positive impact in Local Airbnb Demand of listing i (a one percent increase in the variable Average Market Price is associated with a 0.43 to 0.79 percent increase in Local Airbnb Demand, thus suggesting the presence of significant spatial correlations), positive variations in country-level RGDP are associated with positive variations in Local Airbnb Demand (1.97 to 2.09 elasticities), while increases in

country-level CPI are associated with a negative impact on Local Airbnb Demand (-0.75 to -0.85 elasticities), as are increases in the duration of host's subscription to the platform (albeit with very low marginal impacts). All coefficients are significant at the 99.9% confidence level.

These results corroborate some core findings of earlier research on Airbnb accommodation in New York City prior to the pandemic (Gunter et al., 2020): neighboring Airbnb listings are substitutes for listing i (positive elasticities with respect to Average Market Price), and Airbnb accommodation is an ordinary good (negative elasticities with respect to CPI), as well as a normal and luxury good (positive elasticities >1 with respect to RGDP; Mas-Colell et al., 1995).

3.5.2. Second Stage Results: Price & Demand in Airbnb Setting

Table 3.4. reports the second stage estimation results, estimating the causal impact of Local Airbnb Demand variations on Average Weekly Price. As with the first stage estimations, two models are proposed: a fixed effects model including time-invariant characteristics interacted with seasonal categorical variables (Model 1) and a fixed effects model assuming that time-invariant characteristics are effectively absorbed by the individual fixed effects with their impact not varying over time. For the sake of comparison, both the OLS (labelled "*end"* in Table 4) and the 2SLS estimation results (labelled "*ex"* in Table 4) are presented for each model, showing that OLS fails by systematically biasing coefficient estimates upward and demonstrating the need for a method that properly deals with the endogeneity of the explanatory variable, Local Airbnb Demand.

For 2SLS estimation, various instrumental variable diagnostic statistics are provided, such as the Kleibergen-Paap Underidentification Test, the Kleibergen-Paap Weak Identification Test (Kleibergen & Paap, 2006), and the Cragg-Donald Weak Identification Test (Cragg & Donald, 1993). These statistical tests confirm the validity of our instrumental variable across all models, for instance by very high values on the Kleibergen-Paap Underidentification Test of 1,272.7 in Model 1 and varying from 1,175.7 to 1,483.2[63] across the various specifications of Model 2. As per the discussion of the first stage estimation results, the inclusion of time-invariant characteristics does not significantly increase goodness-of-fit measures, so only Model 2 results are discussed in the following.

[Insert Table 3.4. here.]

Table 3.4. provides novel insights into the determinants of Airbnb prices by specifying the causal relationship between demand and pricing. Indeed, the estimates show a positive relationship between demand and prices, meaning that Airbnb properties facing increasing demand are prone to raise their prices. This result is in line with theoretical expectations. Further, in a market where the offer is constrained or decreasing and demand tends to increase, we expect increases in general price levels according to standard microeconomic theory. This theoretical expectation is also confirmed in the sample, whose time interval spans the pre- to post-pandemic period, when tourism supply not only failed to increase but

[63] The Kleibergen-Paap Weak Identification Test and the Cragg-Donald Weak Identification Test also confirm the validity of our instrumental variable. Moreover, the comparison of the Kleibergen-Paap statistic with the Stock and Yogo (2005) critical values is successfully fulfilled.

even decreased. The coefficients in Table 3.4. show the elasticity of prices in response to demand variations, indicating that a one percent increase in Local Airbnb Demand might result in prices rising by 0.06 to 0.07 percent (all significant at the 99.9% confidence level). In line with expectations, the magnitude of the coefficient decreases as the radius defining the relevant market increases, being at its maximum if r is equal to 250m and at its minimum if r is equal to 1000m. This suggests a higher tendency to increase prices among hosts facing increases in demand for their specific neighborhood (i.e., maybe due to local events) than for hosts facing a general increase in demand over a broader area. Furthermore, in line with Table 3.3., the models' goodness-of-fit measures improve as the radius defining the relevant market gets closer to the treatment dimension (i.e., country level).

The other control variables behave as theoretically expected, since i) Average Weekly Price is spatially autocorrelated with the prices of neighboring listings (with elasticities varying from 0.68 to 0.83, all significant at the 99% confidence level), ii) RGDP positively impact prices (with elasticities varying from 0.37 to 0.42, all significant at the 99.9% confidence level), iii) CPI is positively correlated with prices (with elasticities varying from 0.16 to 0.21, all significant at the 99% confidence level), and iv) duration of the subscription is positively associated with higher prices (still with very low marginal effects).

3.5.3. Pricing: Private (Small Scale) vs Commercial (Large Scale) Hosts

To determine differentials in price to demand elasticities according to the hosts' professionality status, Eqs. 3.3. and 3.4. is estimated separately for two sub-samples — properties managed by Private Hosts (i.e., small scale hosts owning 1 to 2 properties) and properties managed by Commercial Hosts (i.e., large scale hosts owning 3 or more properties) — according to the various specifications of Model 2 (testing the elasticity across different radii while omitting the time-invariant characteristics interacted with seasonal dummies). As in Table 3.4., both the endogenous and the exogenous (2SLS) specifications are presented for each estimate in Table 3.5. For the sake of clarity, Table 3.5. abbreviates Private Hosts with the acronym PR, while Commercial Hosts with the acronym CH. The instrumental variables' statistics provided in Table 3.5. confirm that the instrument is valid, despite achieving lower Kleibergen-Paap Underidentification Test values than the main model (values vary between 938.8 and 1,209.1 for the private host sub-sample and from 289.3 to 373.2 for the commercial host sub-sample). As in Section 3.5.2., the 2SLS model results are discussed in the following.

[Insert Table 3.5. here.]

According to Table 3.5., Commercial hosts (i.e., large scale) vary prices substantially according to demand variations. Indeed, per one percent increase in Local Airbnb Demand, the model predicts a 0.170 to 0.264 percent increase in Average Weekly Price (all coefficients significant at the 99.9% confidence level). In contrast, the pricing response of private hosts (i.e., small scale ones) are less pronounced, with the coefficients not being statistically significant. It is worth noting that the global model's (i.e., the model including private and commercial hosts together) predicted pricing response (i.e., the coefficient of Local Airbnb Demand in Table 4) of an "*average*" Airbnb host lies in the interval of the private/commercial hosts' pricing response coefficients, confirming the validity of the proposed sample differentiation.

This result contributes a novel finding to the flourishing research stream on Airbnb supply side professionalization (Dogru et al., 2020). Building on the widespread acknowledgement that professional hosts have significantly better performance (measured according to monthly revenues or RevPAR; see Deboosere et al., 2019, or Sainaghi et al., 2021, who provide an exhaustive literature review), the present analysis shows that such differences are based on differentials in pricing efficiency, thereby complementing the pioneering results of Li et al. (2016) or the more recent literature on "dynamic pricing" for Airbnb (Abrate et al., 2022; Kwok & Xie, 2019). On the one hand, the model predicts a causal relationship between demand variations and prices for commercial hosts, suggesting that those hosts are able to recognize trends in demand and consequently adjust their prices. On the other hand, the results show that the major pricing components of private hosts are captured by the fixed effects (individual or time fixed effects), by macroeconomic conditions common to the whole industry or to spatial autocorrelation phenomenon, rather than specific local-level fluctuations of demand[64].

These results can be interpreted as a consequence of differing managerial skill levels between the two types of hosts (Abrate et al., 2022). Private hosts, who are generally "regular people", may be unable to benefit from the use of advanced tools (Gibbs, Guttentag, Gretzel, Yao, & Morton, 2018), or only benefit from the tools provided by the platform. Consequently, they tend not to change prices, or even to decrease them (when adopting price-cutting strategies), and fail to exploit the opportunities presented by increasing demand in a capacity-constrained market. Another plausible explanation is that private hosts base their pricing on hedonic-based models rather than adopting a market-based perspective, which would require economic knowledge and time to be effective.

3.5.4. Robustness Checks

This section provides further analyses aimed at corroborating the results according to multiple alternative specifications of the main variables: i.e., i) the time of the pandemic outbreak, ii) the length of the time-interval defining the moving average of Local Airbnb Demand, as well as iii) the threshold distinguishing between private and commercial hosts. In short, all results reported in the previous sections are robust to different variable operationalization and all regression goodness-of-fit metrics, as well as instrumental variable diagnostics, fully confirm the validity of our 2SLS approach.

First, given that the pandemic erupted at different points in time in different European countries in terms of both rising COVID-19 cases and the imposition of restrictions, further robustness checks relax the assumption that global pandemic effects started in the 11th week of 2020 (i.e., the variable $POST_t$=1 if t≥63, =0 otherwise) by employing alternative definitions of the $POST_t$ variable. Both the first stage and second stage (2SLS) models are tested by defining $POST_t$=1 if t≥s, with s=62,64,65 (respectively, the 10th, 12th, and 13th weeks of 2020). Results of first stage models are reported in Appendix A3.1., while Appendix A3.2. shows second stage results. The results of both first and second stage models fully confirm the results reported in Sections 3.5.1. and 3.5.2. Concerning the first stage, the tendency to find higher

[64] In this sense, it is worth to notice that Airbnb provides to all hosts specific tools suggesting the daily pricing to be chosen. See for instance: https://www.forbes.com/sites/ellenhuet/2015/06/05/how-airbnb-uses-big-data-and-machine-learning-to-guide-hosts-to-the-perfect-price/?sh=134d9fe36d49

average elasticities of demand compared to the COVID-19 Stringency Index as r increases is confirmed. Interestingly, and in line with theoretical expectations, the average impact of the COVID-19 Stringency Index on Local Airbnb Demand is higher when interacted with a postulated earlier start of the pandemic (e.g., s=62, compared to s=65).

Second, given that the literature provides no clear evidence defining the past and future planning horizons of hosts, multiple definitions of the parameter f in the definition of the variables Local Airbnb Demand and COVID-19 Stringency Index are tested. Appendix A3.3. shows the results for both first and second stage models (respectively A3.3A for the first stage and A3.3B for the second one), which strongly confirm the main estimates shown in Tables 3.3. and 3.4. On the one hand, the first stage model confirms the negative and strongly significant impact of rising governmental restrictions on Local Airbnb Demand. On the other hand, second stage results confirm a positive relationship between rising demand and Average Weekly Price (although its statistical significance is lower).

Third, recognizing that multiple definitions of private and commercial hosts have been proposed and tested by scholars in the Airbnb literature, two additional models vary the distinguishing property count threshold. The new models are tested using a threshold of 2 (i.e., Private Host = manages one property, otherwise Commercial Host) and 4 (i.e., Private Host = manages up to three properties, otherwise Commercial Host). Appendix A3.4. shows the second stage regression results using the 2SLS approach, presenting private hosts in Appendix A3.4A. and commercial hosts in Appendix A3.4B. Beyond confirming the results shown in Section 3.5.3., this robustness check provides interesting insights into the validity of our results. Appendix A3.4B., indeed, shows that the average demand elasticity of price increases strongly as the threshold increases, thus amplifying the difference between private and commercial hosts.

3.6. Discussions & Conclusions

This study provides several results that are of interest from the perspective of multiple research streams, from which both theoretical and managerial implications can be derived. Its limitations are also addressed and areas for future research are highlighted in the following sub-sections.

This chapter supports the growing literature on the estimation of the impact of the COVID-19 pandemic on tourism-related services demand by providing an empirical analysis of the relationship between governmental response policies (efficiently tracked by the COVID-19 Stringency Index) and the Local Airbnb Demand faced by hosts on the platform, complementing a previous analysis by Hu and Lee (2020), who empirically determined the impact of rising COVID-19 cases on Airbnb reservations. The estimate, beyond shedding light on the impact of national closures on short-term rental demand, provides a methodological contribution to the economic literature on Airbnb (broadly: tourism demand analysis) by employing the novel approach of a difference-in-differences (DID) framework with a continuous treatment at the group level (Callaway et al., 2021).

The adoption of a two-stage least squares (2SLS) approach to estimate the relationship between demand and price introduces a novel instrumental variable for tourism demand, which could solve endogeneity problems when addressing various research questions. The analysis of the relationship describing demand and prices provides further knowledge on the pricing determinants of Airbnb listings, complementing the established literature on short-term rental pricing, which has mainly focused on hedonic-based models describing the impact of listing and/or host level features on prices, typically proxied by ADR (see Sainaghi et al., 2021, for an exhaustive literature review), or on dynamic pricing practices (Abrate et al., 2022; Kwok & Xie, 2019). To this end, this study is one of the first research providing an empirical estimate of how Airbnb hosts are pricing their listings based on demand shocks, further distinguishing agents by the means of their scale of operations.

The results of this research show that an average host on the platform tends to increase its price when facing increasing demand, even when controlling for individual unobserved and time-invariant, seasonal, and time-varying characteristics, macroeconomic factors, and spatial autocorrelation of prices across a given area. This result corroborates theoretical expectations that in a capacity-constrained market – where we can reasonably assume that supply does not vary at the same rate as demand, particularly in this empirical setting that largely covers the COVID-19 period – when demand tends to increase, the general price level also rises. Furthermore, the novelty of this study unveils that this pricing behavior differs between the two main host types distinguished in literature (i.e., private versus commercial; Dogru et al., 2020), with the prices of commercial (large-scale entrepreneurs, to recall the nomenclature in chapter 2) listings being far more responsive to demand variations than properties managed by private host (small-scale entrepreneurs, see again chapter 2). These findings can enrich the growing literature that is thoroughly studying Airbnb supply-side professionalization, which has already shown the tendency of professional hosts to dynamically change their prices more frequently than private ones (Abrate et al., 2022; Kwok & Xie, 2019). Furthermore, the comparison shown in this study resembles and expands the former finding of Boto-Garcia et al. (2021), which have shown that private hosts tend to adopt spatial price mimicking strategies, which have been accounted into the presented econometric models through spatial autocorrelation control variables.

In line with common conceptions of these two host typologies (Dogru et al., 2020), these results can be explained by different degrees of involvement in the Airbnb environment. On the one hand, professional hosts typically invest more time into the platform, enabling them to leverage developed managerial skill sets and industry expertise to track demand variations and efficiently adapt their prices. On the other hand, private hosts typically use Airbnb as an additional source of income, investing less time and effort into the platform, and are not expected to dynamically adapt their prices. As such, the major price variation is captured by seasonal, property-level (namely suggesting a hedonic pricing style) and spatial autocorrelation components (which argues for an increasing usage of pricing suggestion softwares by private hosts rather than commercial ones[65]). Consistent with chapter 2, this study expands the distinction between the different

[65] See: https://www.airbnb.com/help/article/1168?_set_bev_on_new_domain=1669198671_OGY2NDBlYjlhYjE4&locale=en

kind of entrepreneurs on Airbnb platform to another strategic decision. Indeed, if on the one side chapter 2 shows that the entry of professional (i.e., large-scale hosts) sounds to a solid economic reasoning, this study confirm that pricing too responds to the same logic, while, on the other side, private (i.e., small-scale hosts) this does not hold.

Ultimately, all these results are confirmed by several robustness checks, testing the validity of the results according to the main assumptions of the models (i.e., the effective date of the pandemic outbreak, the time-interval of the moving average applied to Local Airbnb Demand, and the threshold distinguishing private and commercial hosts).

3.6.1. Theoretical & Managerial Implications

The results of this research pave the way for future research into this touristic domain, as well as yielding implications for managers and policymakers.

Consistent with one of the main scopes of the study, which aims at providing a novel empirical approach to demand modeling in tourism studies, in applying the novel DID with continuous treatment to explain cross-property (-country) demand variations, while considering the country-level governmental pandemic response as exogenous, this study shows that a new instrumental variable taking into account the endogeneity of demand is available to researchers (as long as data from different countries before and after the pandemic outbreak are available). Future studies adopting the demand for touristic services as a main explanatory variable (whether Airbnb or hotel level demand, or aggregated demand measures at the city, region, or country level) can take advantage of this methodology to efficiently tackle potential endogeneity issues.

Furthermore, relevant insights for policymakers and practitioners can be derived from the analysis[66]. In particular, the additional analysis discriminating between host types confirms (expanding the results in chapter 2) a relevant phenomenon in the sharing economy: the decline of "sharing" and the emergence of "capitalistic hosts" (as named by Dolnicar & Zare, 2020). Bridging the results on the pricing and entry behavior of the distinct kind of hosts (entrepreneurs) active on the platforms, this study confirms that Airbnb supply is clearly segmented, in the sense that way different typologies of hosts are present within the same side of the platforms. In this vein, policymakers must be informed on the fact that Airbnb has departed the traditional sharing economy framework (Franken & Schor, 2017) embracing a "capitalistic" viewpoint (Dolnicar & Zare, 2020). To this end, if on the one side, as reported in chapter 2, these transition makes Airbnb a suitable enabler for structured entrepreneurs too (and not only people seeking to additional income exploiting idle assets), on the other side, the presence of professionals with larger domain expertise onto the platform calls for a careful policy design aimed at limiting and or regulating the activity of such professionals. In line with this, an emerging literature from Chen et al. (2022a) or Chen et al. (2022b), has shown, thanks to an experimental study using a One-Host-One-Home Policy in the US, how commercial service providers are distorting competition on Airbnb supply

[66] Out of the scope of the research, this study has also implications regarding the strategies to recover from COVID-19, or additional insights on the elasticity of touristic demand to government response to Pandemic diffusion. To this end, the development of effective tourism rebound measures necessitate empirical quantification of the losses caused not only by the diffusion of COVID-19 but also by the enacted policy responses. This analysis provides an effective methodology to evaluate such impacts, as well as an empirical application to the short-term rental context

side and generating negative externalities on societal welfare. On the other hand, sharing-economy practitioners, must be aware of the different behavior of the service providers active onto the platform. Indeed, to the extent that capitalistic actors typically outperform other players (Sainaghi et al., 2021) practitioners should know that such differences may be derived from a different pricing management, with the dynamic pricing strategies adopted by commercial hosts securing higher profits (Sainaghi et al., 2021) compared to the "mimicking" (to recall also Boto-Garcia et al., 2021) strategies of private hosts.

Finally, the study has further theoretical implications for future research seeking to understand how move prices in a sharing economy market. The finding that higher prices are significantly associated with increasing local demand shows that pricing variation is not only based on seasonal or hedonic factors, and that a market-based perspective must also be taken into account.

3.6.2. Limitations & Future Research

Despite having shown that the methodology introduced in this paper can be of interest to future research on tourism-demand related topics, this research is not exempt from limitations, which themselves can suggest further avenues for research. Firstly, this analysis is confined to the short-term rental market; further analyses on the behavior of traditional hospitality suppliers would allow for an in-depth comparison between the competitive practices of short-term rentals and those of hotels. Secondly, despite robustness analyses strongly confirming the validity of the results, future endeavors could benefit from some methodological refinement of the definition of "local" demand, which does not have a clear definition among researchers, and of the definition of the moving average filter. Finally, further distinctions of property sub-samples (e.g., distinguishing rural versus urban areas, entire versus shared apartments, or weekends versus weekdays) could be of interest to researchers, managers, and policymakers in the tourism domain.

References – Chapter 3

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Tables – Chapter 3

Table 3.1. Distribution of selected listings, reserved nights, and revenues (in USD) by country (2019 vs. 2020).

Country	# Properties	Reserved Nights 2020	Reserved Nights 2019	Revenues 2020 (in USD)	Revenues 2019 (in USD)
Italy	35,213	1,655,894	3,379,621	164,491,118.00	344,069,870.00
France	29,436	1,725,702	2,586,933	200,703,468.00	280,994,097.00
Spain	16,862	1,014,078	2,032,167	118,672,080.00	231,353,327.00
Germany	9,562	753,611	1,104,026	69,838,194.00	96,902,511.00
Portugal	6,582	453,026	962,154	40,605,992.00	91,137,285.00
Greece	5,795	208,072	462,018	21,568,822.00	47,927,944.00
Croatia	5,139	122,496	317,168	12,510,346.00	31,887,826.00
Poland	2,905	248,400	422,833	17,600,777.00	29,169,039.00
Netherlands	2,592	292,036	424,269	35,061,007.00	52,816,239.00
Belgium	2,084	192,899	299,894	24,501,229.00	34,286,179.00
Ireland	1,776	124,048	193,306	16,193,901.00	22,872,293.00
UK	1,426	31,121	194,931	4,607,904.00	39,846,088.00
Denmark	1,397	84,221	134,716	8,900,502.00	15,199,921.00
Austria	1,260	95,486	202,264	10,408,717.00	21,157,930.00
Romania	1,092	46,981	99,729	3,001,229.00	6,210,708.00
Sweden	1,064	61,992	97,746	7,532,364.00	10,985,076.00
Hungary	980	63,966	187,669	4,169,950.00	14,374,946.00
Bulgaria	914	26,596	49,293	1,924,895.00	3,140,865.00
Finland	677	51,437	66,733	6,211,200.00	7,600,403.00
Malta	505	31,986	70,423	3,595,737.00	7,363,913.00
Slovenia	394	26,815	46,997	2,881,376.00	4,734,182.00
Lithuania	341	16,088	29,198	1,074,361.00	1,813,306.00
Slovakia	268	15,879	27,228	1,133,754.00	1,827,550.00
Estonia	232	15,891	29,151	1,346,186.00	2,659,710.00
Latvia	182	10,376	21,343	761,888.00	1,608,744.00
Luxembourg	39	4,308	6,620	393,498.00	578,868.00
Switzerland	2	17	88	4,188.00	8,373.00

Notes:

a) Data Source: AirDNA.
b) Data were arranged by means of Python (using *Pandas* library for data management).
c) The number of properties contains those properties recorded in the final dataset, as explained in Section 3.1.
d) Countries are sorted in descending order according to the number of properties recorded.

Table 3.2. Descriptive Statistics.

Variable Group	Variable	Mean	Std. Dev.	Min	Max
Dependent Variable	Average Weekly Price (AWP) (i,t)	100.52	80.03	20.14	754.43
Explanatory and Instrumented Variable	Local Airbnb Demand (LAD) (i,250m,t)	65.78	118.99	1.00	1,030.43
	Local Airbnb Demand (LAD) (i,500m,t)	188.48	348.00	1.00	2,386.57
	Local Airbnb Demand (LAD) (i,750m,t)	344.83	634.73	1.00	3,963.86
	Local Airbnb Demand (LAD) (i,1000m,t)	510.67	924.65	1.00	5,206.57
Instrumental Variable	COVID-19 Stringency Index (CSI) (t,g) *	55.56	12.93	2.97	96.30
Spatial Controls	Average Market Price(i,250m,t)	78.83	68.96	0.00	748.86
	Average Market Price(i,500m,t)	88.28	65.08	0.00	748.86
	Average Market Price(i,750m,t)	92.50	62.31	0.00	748.86
	Average Market Price(i,1000m,t)	95.35	60.62	0.00	735.29
	Number of Competitors(i,250m)	15.77	27.46	0.00	180.00
	Number of Competitors(i,500m)	48.16	81.76	0.00	476.00
	Number of Competitors(i,750m)	89.40	150.01	0.00	787.00
	Number of Competitors(i,1000m)	133.46	219.52	0.00	1,033.00
Macroeconomic Controls	RGDP(i,g,t)	28,155.79	9071.53	6600.00	83,640.00
	CPI(i,g,t)	111.74	3.50	99.55	127.04
Property-Level Controls	Beds(i)	4.18	2.65	1.00	16.00
	Photos(i)	24.00	17.05	1.00	286.00
	Host's Properties(i)	3.23	9.19	1.00	619.00
	Multiplatform(i)	0.12	-	0	1
	Experience(i,t)	163.60	89.38	0.00	587.00
	Cancellation Policy(i)	0.86	-	0	1
	Instantbook(i)	0.69	-	0	1
	MidLong Rent(i)	0.001	-	0	1

Notes:

a) Data Sources: AirDNA, Eurostat, Our World in Data.
b) Subscripts: i = Property, t = Time (Year-Week), g = Country, 250m/500m/750m/1000m = Radius r defining the relevant market.
c) The table was generated by means of Stata 17 (command *sum*).
d) * = The descriptive statistics are provided from $t=63$ onwards.

Table 3.3. First Stage Results

Table 3.3A. – Full model with r=500m [Model 1]

	Spec. 2 r = 500m
ln COVID-19 Stringency Index(g,t)*$POST_{63}$	-0.149***
	(0.004)
ln Average Market Price(i,500m,t)	0.628***
	(0.002)
ln Number of Competitors(i,500m)*Season(t)	Yes
ln RGDP(g,t)	2.082***
	(0.018)
ln CPI(g,t)	-1.020***
	(0.070)
ln Beds(i)*Season(t)	Yes
ln Photos(i)*Season(t)	Yes
ln Host's Properties(i)*Season(t)	Yes
Multiplatform(i)*Season(t)	Yes
ln Experience(i,t)	Yes
Cancellation Policy(i)*Season(t)	Yes
Instantbook(i)*Season(t)	Yes
MidLong Rent(i)*Season(t)	Yes
Constant	-15.045***
	(0.294)
Time Fixed Effects	Yes
Individual Fixed Effects	Yes
Number of Observations	2,205,347
Robust Standard Errors	Yes
F	3,419.176
R^2 Adjusted	0.983
R^2 Within	0.085
R^2 Within Adjusted	0.085
AIC	-340,204.744
BIC	-339,776.127

Notes:

a) Subscripts: *i* = Property, *t* = Time (Year-Week), *g* = Country, 500m = Radius *r* defining the relevant market. Individual Fixed Effects stands for property-level (i) fixed effects included in the model.
b) Dependent variable = ln Local Airbnb Demand(i,r,t).
c) Estimates were generated by the means of Stata 17 (command *reghdfe*).
d) *** p<0.001, ** p<0.01, * p<0.5, + p<0.1.
e) The reference baseline of time-invariant variables interacted with Season(t) is autumn.
f) Coefficients of the full model have been excluded due to space constraints, yet are available from the authors upon request.

Table 3.3B. – Reduced model with r=250m/500m/750m/1000m [Model 2]

	Spec. 1 r = 250m	Spec. 2 r = 500m	Spec. 3 r = 750m	Spec. 4 r = 1000m
ln COVID-19 Stringency Index(g,t)*$POST_{63}$	-0.133***	-0.146***	-0.154***	-0.155***
	(0.004)	(0.004)	(0.004)	(0.004)
ln Average Market Price(i,r,t)	0.434***	0.615***	0.714***	0.790***
	(0.002)	(0.002)	(0.002)	(0.003)
ln RGDP(g,t)	1.982***	2.085***	2.010***	1.969***
	(0.017)	(0.018)	(0.019)	(0.019)
ln CPI(g,t)	-0.784***	-0.851***	-0.752***	-0.747***
	(0.068)	(0.071)	(0.071)	(0.071)
ln Experience(i,t)	-0.012***	-0.015***	-0.016***	-0.016***
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-14.640***	-15.585***	-15.383***	-15.109***
	(0.286)	(0.294)	(0.293)	(0.292)
Time Fixed Effects	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes
Number of Observations	2,205,346	2,205,346	2,205,346	2,205,346
Robust Standard Errors	Yes	Yes	Yes	Yes
F	13,851.453	19,098.485	21,018.121	22,850.216
R^2 Adjusted	0.975	0.983	0.986	0.988
R^2 Within	0.055	0.076	0.087	0.097
R^2 Within Adjusted	0.055	0.076	0.087	0.097
AIC	-495,716.920	-317,481.635	-263,401.673	-240,072.580
BIC	-495,641.282	-317,405.997	-263,326.035	-239,996.941

Notes:

a) Subscripts: *i* = Property, *t* = Time (Year-Week), *g* = Country, 250m/500m/750m/1000m = Radius *r* defining the relevant market. Individual Fixed Effects stands for property-level (i) fixed effects included in the model.

b) Dependent variable = ln Local Airbnb Demand(i,r,t).

c) Estimates were generated by the means of Stata 17 (command *reghdfe*).

d) *** p<0.001, ** p<0.01, * p<0.5, + p<0.10.

Table 3.4. Second Stage Results.

Table 3.4A. – Full model with r=500m [Model 1]

	r = 500m	
	Spec. 2 end OLS	Spec. 2 ex 2SLS
ln Local Airbnb Demand(i,g,500m,t)	0.162***	0.123***
	(0.001)	(0.016)
ln Average Market Price(i,500m,t)	0.681***	0.706***
	(0.002)	(0.010)
ln Number of Competitors(i,500m)*Season(t)	Yes	Yes
ln RGDP(g,t)	0.119***	0.232***
	(0.011)	(0.035)
ln CPI(g,t)	0.198***	0.000
	(0.041)	(.)
ln Beds(i)*Season(t)	Yes	Yes
ln Photos(i)*Season(t)	Yes	Yes
ln Host's Properties(i)*Season(t)	Yes	Yes
Multiplatform(i)*Season(t)	Yes	Yes
ln Experience(i,t)	Yes	Yes
Cancellation Policy(i)*Season(t)	Yes	Yes
Instantbook(i)*Season(t)	Yes	Yes
MidLong Rent(i)*Season(t)	Yes	Yes
Constant	-0.966***	
	(0.172)	
Time Fixed Effects	Yes	Yes
Individual Fixed Effects	Yes	Yes
Number of Observations	2,205,347	2,205,347
Robust Standard Errors	Yes	Yes
F	9,578.177	6,655.549
R^2 Adjusted	0.938	0.209
R^2 Within	0.242	
R^2 Within Adjusted	0.242	
R^2 Uncentered		0.239
AIC	-2,111,471.237	-2,103,789.793
BIC	-2,111,042.619	-2,103,386.388
Kleibergen-Paap Underid. Test (rk LM)		1,272.740
Kleibergen-Paap Weak Id. Test (Wald F)		1,235.318
Cragg-Donald Weak Id. Test (Wald F)		2,924.894

Notes:

a) Subscripts: *i* = Property, *t* = Time (Year-Week), *g* = Country, 500m = Radius *r* defining the relevant market. Individual Fixed Effects stands for property-level (i) fixed effects included in the model.
b) Dependent variable = ln Average Weekly Price(i,t).
c) Estimates were generated by the means of Stata 17 (command *ivreghdfe* for 2SLS estimations and command *reghdfe* for OLS estimations).
d) *** p<0.001, ** p<0.01, * p<0.5, + p<0.10
e) end = Endogenous, ex = Exogenous (i.e., 2SLS approach).
f) The reference baseline of time-invariant variables interacted with Season(t) is autumn.
g) The coefficient of ln CPI(g,t) is partialled out by the *ivreghdfe* estimation command because of collinearity with the fixed effects.
h) Coefficients of the full model have been excluded due to space constraints, yet are available from the authors upon request.

Table 3.4B. – Reduced model with r=250m/500m/750m/1000m [Model 2]

	r = 250m		r = 500m		r = 750m		r = 1000m	
	Spec. 1 end OLS	Spec. 1 ex 2SLS	Spec. 2 end OLS	Spec. 2 ex 2SLS	Spec. 3 end OLS	Spec. 3 ex 2SLS	Spec. 4 end OLS	Spec. 4 ex 2SLS
ln Local Airbnb Demand(i,g,r,t)	0.165***	0.075***	0.164***	0.072***	0.163***	0.071***	0.162***	0.057***
	(0.001)	(0.018)	(0.001)	(0.016)	(0.001)	(0.015)	(0.001)	(0.015)
ln Average Market Price(i,500m,t)	0.639***	0.678***	0.697***	0.753***	0.726***	0.792***	0.742***	0.825***
	(0.002)	(0.008)	(0.002)	(0.010)	(0.002)	(0.011)	(0.002)	(0.012)
ln RGDP(g,t)	0.211***	0.417***	0.152***	0.378***	0.129***	0.351***	0.128***	0.370***
	(0.011)	(0.037)	(0.011)	(0.036)	(0.011)	(0.033)	(0.011)	(0.032)
ln CPI(g,t)	0.161***	0.000	0.198***	0.000	0.209***	0.000	0.186***	0.000
	(0.042)	(.)	(0.041)	(.)	(0.041)	(.)	(0.041)	(.)
ln Experience(i,t)	0.003***	0.002*	0.004***	0.003***	0.005***	0.003***	0.006***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-1.164***		-1.306***		-1.416***		-1.486***	
	(0.173)		(0.172)		(0.171)		(0.170)	
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	2,205,346	2,205,346	2,205,346	2,205,346	2,205,346	2,205,346	2,205,346	2,205,346
Robust Standard Errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F	48,815.521	37,369.489	55,072.584	42,063.993	57,398.353	43,128.609	58,561.251	43,590.402
R^2	0.938	0.207	0.939	0.221	0.940	0.227	0.940	0.224
R^2 Adjusted	0.936	0.176	0.937	0.190	0.938	0.196	0.938	0.194
R^2 Within	0.220		0.235		0.242		0.244	
R^2 Within Adjusted	0.220		0.235		0.242		0.244	
R^2 Uncentered		0.207		0.221		0.227		0.224
AIC	-2048768.489	-2012682.668	-2092268.882	-2050714.823	-2110696.575	-2067716.937	-2117352.492	-2061060.688
BIC	-2048692.850	-2012632.243	-2092193.244	-2050664.397	-2110620.937	-2067666.511	-2117276.854	-2061010.262
Kleibergen-Paap Underid. Test (rk LM)		1,175.762		1,273.064		1,450.041		1,483.185
Kleibergen-Paap Weak Id. Test (Wald F)		1,134.378		1,232.496		1,412.884		1,448.173
Cragg-Donald Weak Id. Test (Wald F)		2,584.863		2,851.966		3,179.501		3,203.762

Notes:

a) Subscripts: *i* = Property, *t* = Time (Year-Week), *g* = Country, 250m/500m/750m/1000m = Radius *r* defining the relevant market. Individual Fixed Effects stands for property-level (i) fixed effects included in the model. Dependent variable = ln Average Weekly Price(i,t).

b) Estimates were generated by the means of Stata 17 (command *ivreghdfe* for 2SLS estimations and command *reghdfe* for OLS estimations).

c) *** p<0.001, ** p<0.01, * p<0.5, + p<0.10.

d) end = Endogenous, ex = Exogenous (i.e., 2SLS approach).

e) The coefficient of ln CPI(g,t) is partialled out by the *ivreghdfe* estimation command because of collinearity with the fixed effects.

Table 3.5. Pricing: Commercial vs Private Hosts

	r = 250m				r = 500m				r = 750m				r = 1000m			
	S1 end PR	S1 end CH	S1 ex PR	S1 ex CH	S2 end PR	S2 end CH	S2 ex PR	S2 ex CH	S3 end PR	S3 end CH	S3 ex PR	S3 ex CH	S4 end PR	S4 end CH	S4 ex PR	S4 ex CH
ln Local Airbnb Demand(i,r,t,f)	0.174***	0.125***	-0.011	0.264***	0.172***	0.128***	0.001	0.213***	0.170***	0.133***	0.015	0.192***	0.168***	0.136***	0.006	0.170***
	(0.001)	(0.001)	(0.021)	(0.039)	(0.001)	(0.001)	(0.019)	(0.035)	(0.001)	(0.001)	(0.017)	(0.038)	(0.001)	(0.001)	(0.016)	(0.039)
ln Average Market Price(i,r,t)	0.512***	0.893***	0.592***	0.830***	0.570***	0.984***	0.674***	0.929***	0.604***	1.016***	0.713***	0.972***	0.622***	1.031***	0.749***	1.004***
	(0.002)	(0.003)	(0.009)	(0.018)	(0.002)	(0.003)	(0.012)	(0.023)	(0.002)	(0.004)	(0.012)	(0.028)	(0.002)	(0.004)	(0.013)	(0.032)
ln RGDP(g,t)	0.146***	0.407***	0.519***	0.200*	0.096***	0.346***	0.465***	0.208**	0.081***	0.277***	0.413***	0.205**	0.081***	0.268***	0.419***	0.241**
	(0.012)	(0.026)	(0.041)	(0.079)	(0.012)	(0.027)	(0.040)	(0.076)	(0.012)	(0.028)	(0.035)	(0.078)	(0.012)	(0.028)	(0.034)	(0.078)
ln CPI(g,t)	0.062	0.275***	0.000	0.000	0.120*	0.175*	0.000	0.000	0.137**	0.209*	0.000	0.000	0.121**	0.171*	0.000	0.000
	(0.048)	(0.080)	(.)	(.)	(0.048)	(0.082)	(.)	(.)	(0.047)	(0.083)	(.)	(.)	(0.047)	(0.083)	(.)	(.)
ln Experience(i,t)	0.002*	0.005***	-0.000	0.007***	0.003***	0.006***	0.001	0.007***	0.004***	0.005***	0.002*	0.006***	0.005***	0.007***	0.002**	0.007***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Constant	0.548**	-5.257***			0.241	-4.809***			0.002	-4.529***			-0.112	-4.421***		
	(0.205)	(0.308)			(0.202)	(0.308)			(0.200)	(0.308)			(0.199)	(0.310)		
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	1,629,176	576,161	1,629,176	576,161	1,629,176	576,161	1,629,176	576,161	1,629,176	576,161	1,629,176	576,161	1,629,176	576,161	1,629,176	576,161
Robust Standard Errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F	28,412	22,448	17,323	23,024	33,257	26,259	20,388	27,866	35,542	25,311	21,998	26,590	36,946	24,316	22,810	25,416
R^2	0.940	0.934	0.114	0.312	0.942	0.934	0.142	0.319	0.943	0.933	0.162	0.317	0.943	0.932	0.162	0.313
R^2 Adjusted	0.938	0.932	0.078	0.285	0.940	0.931	0.108	0.292	0.941	0.930	0.128	0.290	0.941	0.930	0.129	0.286
R^2 Within	0.174	0.335			0.199	0.328			0.210	0.321			0.215	0.315		
R^2 Within Adjusted	0.174	0.335			0.199	0.328			0.210	0.321			0.215	0.315		
R^2 Uncentered			0.114	0.312			0.142	0.319			0.162	0.317			0.162	0.313
AIC	-1,606,163	-487,110	-1,491,962	-467,504	-1,656,418	-480,890	-1,544,725	-473,400	-1,679,231	-474,961.634	-1,582,322	-471,443	-1,690,579	-469,608	-1,583,708	-468,458
BIC	-1,606,089	-487,042	-1,491,913	-467,459	-1,656,344	-480,823	-1,544,676	-473,354	-1,679,158	-474,894.050	-1,582,272	-471,398	-1,690,505	-469,541	-1,583,659	-468,412
Kleibergen-Paap Underid. Test (rk LM)			938.847	289.285			942.928	373.219			1,156.347	338.366			1,209.086	327.977
Kleibergen-Paap Weak Id. Test (Wald F)			900.491	285.807			907.095	373.450			1,120.382	339.877			1,172.056	331.745
Cragg-Donald Weak Id. Test (Wald F)			1,950.059	711.563			2,053.014	891.359			2,463.082	796.561			2,532.367	763.370

Notes:

a) Subscripts: *i* = Property, *t* = Time (Year-Week), *g* = Country, 250m/500m/750m/1000m = Radius *r* defining the relevant market. Individual Fixed Effects stands for property-level (i) fixed effects included in the model. Dependent variable = ln Average Weekly Price(i,t).

b) Estimates were generated by the means of Stata 17 (command *ivreghdfe* for 2SLS estimations and command *reghdfe* for OLS estimations).

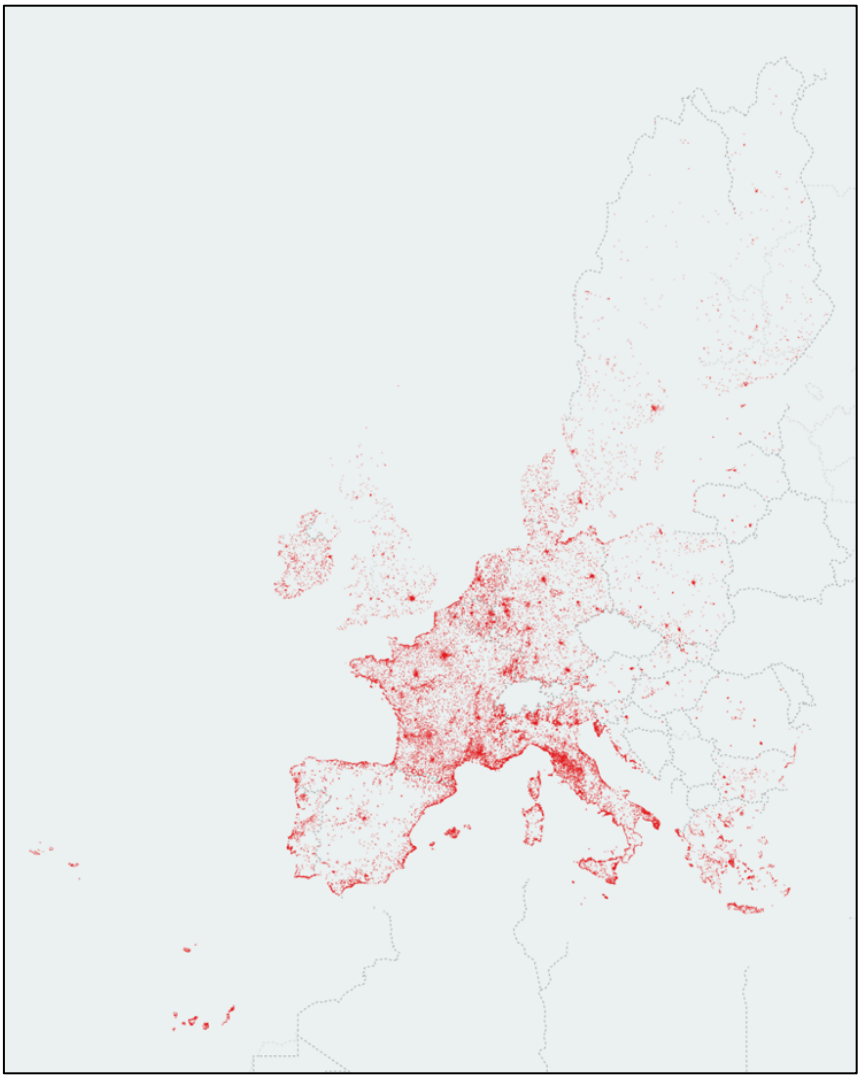
c) *** p<0.001, ** p<0.01, * p<0.5, + p<0.10.

d) end = Endogenous, ex = Exogenous (i.e., 2SLS approach).

e) The coefficient of ln CPI(g,t) is partialled out by the *ivreghdfe* estimation command because of collinearity with the fixed effects.

Figures – Chapter 3

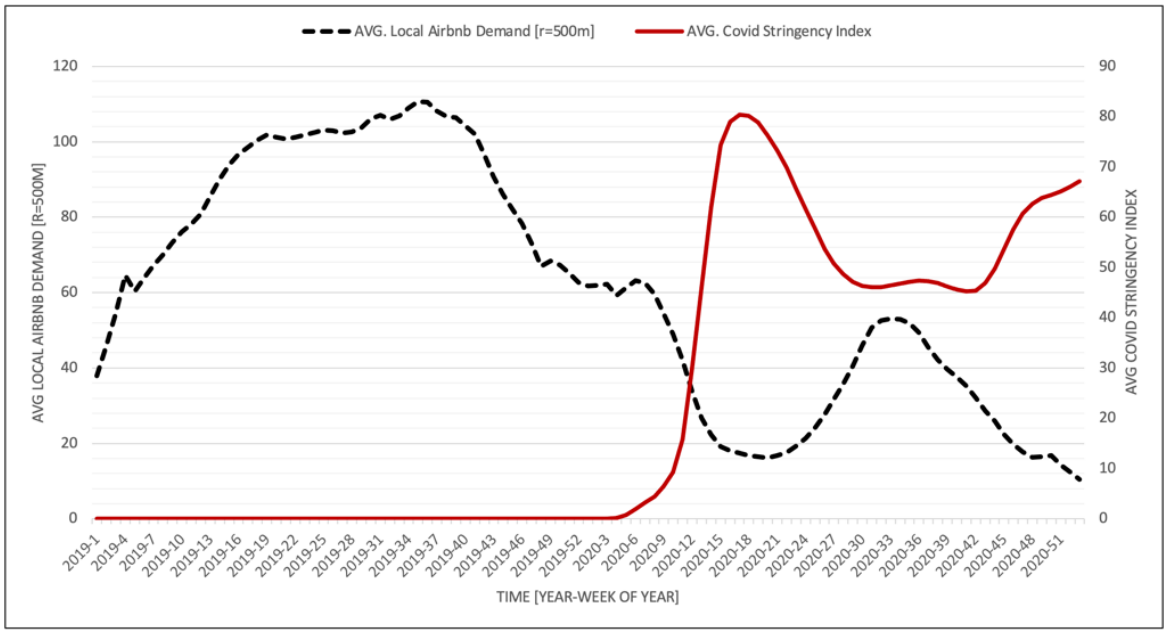
Figure 3.1. Geographical distribution of Airbnb listings within the sample (continuously active listings in 2019 and 2020).



Notes:

a) Data Source: AirDNA.
b) The properties shown in the maps are those included in the final dataset, as explained in Section 3.1.
c) The map was generated on Kepler.gl (https://kepler.gl).

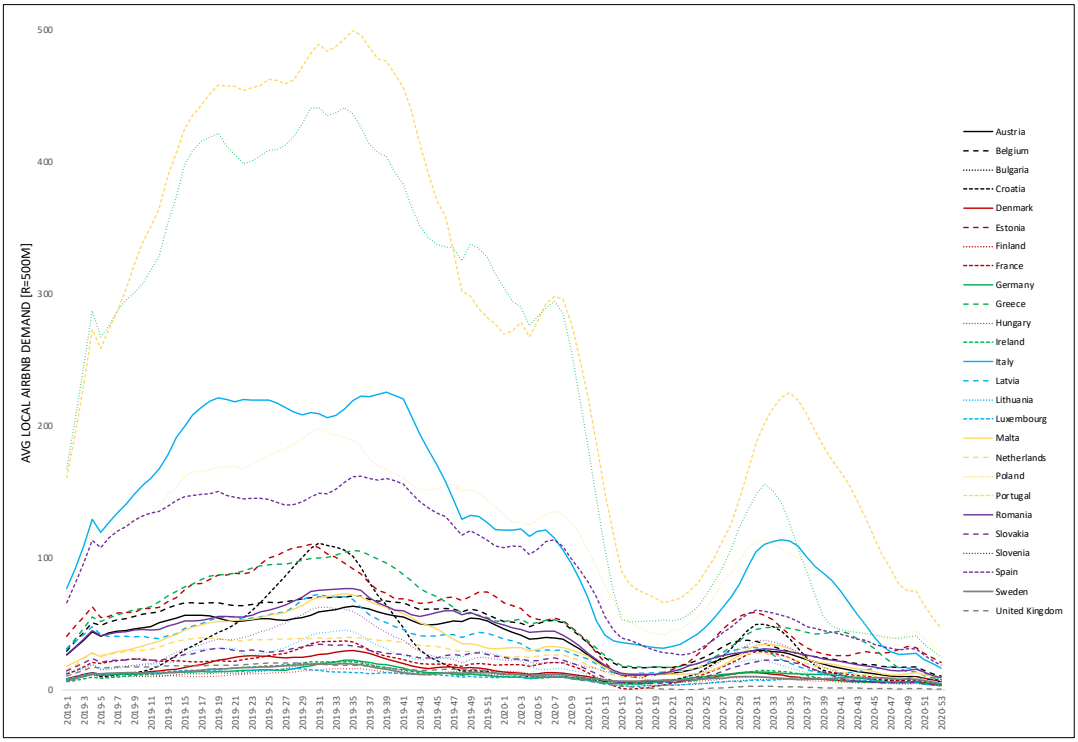
Figure 3.2. Covid-19 Stringency Index and Local Airbnb Demand.



Notes:

a) Data Sources: AirDNA (for Local Airbnb Demand) and Our World in Data (for COVID-19 Stringency Index, see Hale et al., 2021).
b) Data were manipulated using Python (*Pandas* library) and the chart was generated with Microsoft Excel.
c) "AVG Local Airbnb Demand" is the European average value at time *t* of the variable *Local Airbnb Demand* using the radius of 500m, "AVG COVID Stringency Index" is the European average value at time *t* of the variable *COVID-19 Stringency Index*.

Figure 3.3. Visual Inspection for Parallel Trend Assumption.



Notes:

a) Data Source: AirDNA.
b) Data were manipulated using Python (*Pandas* library) and the chart was generated with Microsoft Excel.
c) AVG Local Airbnb Demand is the average value at time *t* of *Local Airbnb Demand* using the radius of 500m.

CHAPTER 4

The Role of Digital Platforms in developing Entrepreneurship in Marginal Economic Destinations

Abstract

This chapter enters the flourishing debate about the effects of digital platforms on local economic conditions, estimating how the entry of a home-sharing platform affects the entrepreneurial activity and the global economic outlook in marginal destinations. Compared to the extant literature, which has mainly provided empirical analyses in urban centers, this study contends that when economic conditions are declining, namely in marginal areas, the entry of the platform, acting as External Enabler, can stimulate the entrepreneurial activity and consequently the local economy of marginal areas. These arguments are tested on the case of 270 Italian Borghi observed from 2009 to 2019 and the respective entry of Airbnb employing a quasi-experimental study with a panel event study approach. The results show that the entry of the platform causes significant increases in the entrepreneurial activity (income from entrepreneurial activity, per capita income from entrepreneurial activity and number of active firms) with mechanisms permuting thought all the value chain, starting from downward services (e.g., restoration) to upstream sectors (e.g., agriculture). Finally, potential policy-maker implications are discussed.

Keywords

Platforms Economics, Home Sharing, Entrepreneurship, Rural Areas, Difference in Difference.

Credits & Acknowledgments

This chapter is extrapolated from a paper jointly written with Prof. Elisabetta Raguseo (Politecnico di Torino) and Prof. Emilio Paolucci (Politecnico di Torino).

The author(s) thanks to FULL – The Future Urban Legacy Lab for its financial support and the Chamber of Commerce of Piemonte for the provision of additional data. I am grateful to the attendees of the XXXIII AiIG Annual Scientific Meeting in Rome and the participants to the workshop "The Economics of Airbnb" held in Nice (December 2022) for the valuable suggestions.

4.1. Introduction

Compared to the previous chapters, which have analyzed how the contextual market's conditions affect the platform and the subjects participating to the digital market (i.e., entrepreneurs producing services and visitors demanding for short-term stays), this, last, chapter reverses the point of view of the analysis, assessing how the platform affects the local market conditions. In doing so, and in line with the common thread of this dissertation, studying a spatially localized platform, the following study enters the rising and debated literature on the externalities generated by digital platforms on local economic conditions, which has produced a conspicuous set of findings, sometimes contrasting (Zervas et al., 2017; Farronato & Fradkin, 2022; Barron et al., 2021; Chen et al., 2022; Burtch et al., 2018; Carrasco-Farrè et al., 2022).

Grounding on the extant literature, this chapter extends and complements the previous findings by adopting a novel point of view. Indeed, while researchers have produced several contributions estimating the impact of digital platforms' entry on entrepreneurial activity (Burtch et al., 2018; Agrawal et al., 2015; von Briel et al., 2018) or on local economic welfare (Barron et al., 2021; Chen et al., 2022; Farronato & Fradkin, 2022) in economically developed cities (mainly showing negative externalities), this study offers a picture of such effects in marginal economic conditions, experiencing a declining economic outlook. In order to carry on this analysis, this chapter recalls the theoretical framework of External Enabler (Davidsson, 2015; previously used in the second chapter) applying it to the context of the Italian Borghi given that they closely represent the idea of marginal economic areas. In particular, according to the data on the Italian Borghi, the effects of Airbnb diffusion on the local entrepreneurial activity, and the corresponding economic gains, have been analyzed in a quasi-experimental setting. Thanks to its novel point of view, this study envisages a relevant contribution to the understanding of the effects of digital platforms on local economic conditions, providing novel elements in the hand of policymakers that are planning the recovery of marginal/rural areas (especially in the post-Pandemic phase). In particular, conversely to the extant literature which has mainly provided a negative point of view on Airbnb spillover effects on local residents and hospitality businesses (Zervas et al., 2017; Farronato & Fradkin, 2022; Barron et al., 2021; Chen et al., 2022; Carrasco-Farrè et al., 2022), this study envisages that in specific circumstances (i.e., marginal areas) the platform creates room for novel entrepreneurs, fostering local economy.

The rest of the chapter is organized as follows. Section 4.2. briefly revises the major contributions to the literature of platforms and entrepreneurship, and home-sharing platforms and local economic conditions, Section 4.3. introduces the empirical testbed of the Italian Borghi, Section 4.4. presents the data and the empirical methodologies, Section 4.5. illustrates the results and a large battery of robustness checks, while Section 4.6. provides a discussion of the results and a sub-section with implications for policy makers. Finally, Section 4.7. concludes the research, illustrating also the limitations as well as the future study which can build upon this.

4.2. Related Literature

This study merges two strands of literature, collocating itself in the middle between the effects of home-sharing on local economic welfare, on the one side, and, primarily, the relationship between sharing economy digital platforms and entrepreneurial activity, on the other.

In this vein, this section first discusses why, generally, digital platforms can affect entrepreneurial activity, then revises the main contributions on the literature about home-sharing externalities and finally, ensembles the two streams by highlighting the novel contributions of this work.

4.2.1 Digital platforms as enablers of entrepreneurial activities (in marginal economic conditions)

In line with a consistent body of literature (Agrawal et al., 2018; Davidsson, 2015; von Briel et al., 2018; Burtch et al., 2018; Acs & Armington, 2006; Block & Koellinger, 2009) there are different argumentations about *whether*, and *how*, a digital platform (in this case Airbnb) can affect entrepreneurs' decisions to embark in novel activities. The extant literature, indeed, identifies different, interrelated, mechanisms through which platforms can shape entrepreneurs' acts, pointing out the digital service provider as either facilitator (Agrawal et al., 2018; Davidsson, 2015; von Briel et al., 2018) or deterrent (Burtch et al., 2018; Acs & Armington, 2006; Block & Koellinger, 2009).

The literature about the entrepreneurial process and the scientific construct of entrepreneurial *opportunities* (Shane, 2000; Gartner, 1988; Shane & Venkataraman, 2000; Alvarez et al., 2013; Dutta & Crossan, 2005; Srinivasan & Venkataraman, 2017; Davidsson, 2015) provides suitable argumentations to derive theoretical explanations on whether the diffusion of a digital platform (in marginal economic areas) stimulates the decision of entrepreneurs to start new activities. Indeed, to the end that entrepreneurial opportunities are situations in which "*new goods, services, raw materials, and organizing methods can be introduced and sold at greater than their cost of production*" (Casson, 1982), this study contends that the diffusion of online platforms, allowing for a more efficient strategic deployment of resources (Kretschmer et al., 2022), can positively affect entrepreneurs' decisions as long as new services can be introduced with lower entry barriers. Particularly, consistent with the idea that entrepreneurs' decisions to embark in new activities derive from a process of identification and exploitation of such opportunities (Shane, 2000; Shane & Venkataraman, 2000) the theoretical framework of Davidsson (2015) of *External Enabler* provides an appropriate theoretical argumentation in this context. Indeed, to the extent that an *External Enabler* is "*an external circumstance which – by affecting supply, demand, costs, prices or payoff structures – can play an essential role in eliciting and/or enabling a variety of venture development attempts by several actors*" (Davidsson, 2015, p. 684), the entry of a digital platform (in a marginal economic areas) can constitutes an opportunity enabler either on the supply side or on the demand one. First, as said above, the entry of home-sharing digital platforms allows prospective entrepreneurs to enter specific market segments with lower costs, e.g., rentals in the case of Airbnb, to the extent that the platform offer a service able to orchestrate resources with lower

efforts[67] (Kretschmer et al., 2022). Consistently, on the demand side, the platform enables entrepreneurial *opportunities* given the wider market exposure that a global platform can provide (Gawer & Cusumano, 2002; Parker et al., 2016) thus fostering prospective entrepreneurs to enter the market as long as greater profit opportunities are perceived. In this manner, these theoretical argumentations claims that online platforms do have a relevant role in determining processes of opportunities creation, consistently with the recent contribution of von Briel et al., (2018) defining digital platforms as external enablers of new ventures creation in the IT sector and beyond. Furthermore, this study argues (and test) that that these effects are not only related to the industrial sector in which the external enabler (i.e., the digital platform Airbnb in our case) is operating but can permute through all the industrial sectors potentially available within the local market.

Multiple contributions have provided an empirical testbed for such theoretical arguments. Closely tied with the aim of this research, Burtch et al. (2018) provided an examination of the effects of Uber's entry on the entrepreneurial activity in US main cities, showing that a decrease in the entrepreneurial activity, mainly concentrated in low-quality segments, is caused as of the roll-out of Uber in a city, thus pointing out the platform (i.e., Uber) as deterrent rather than *External Enabler* of entrepreneurial processes. While findings of Burtch et al. (2018) can be explained because the diffusion of gig-economy platforms can increase the opportunity costs faced by prospective entrepreneurs as they offer a viable and remunerable activity (Acs & Armington, 2006; Block & Koellinger, 2009), particularly to underemployed people (Block & Koellinger, 2009), there are other empirical applications supporting the external enablement theory. Indeed, to the end that the digital platforms allow entrepreneurs to strategically re-allocate slack resources such as time (Agrawal et al., 2018), the roll-out of such digital service providers can enhance the entrepreneurial activity.

4.2.2. The effects of home-sharing platforms on local economic conditions

Home-sharing platforms (the focus of this study) have been, in the last years, widely studied by researchers given the relevant externalities generated well beyond the touristic sector, which envisage a wider discussion spanning from its effects on entrepreneurial activity to the effects on societal welfare. Although the platform has been, indeed, recognized as a valid testbed for prospective entrepreneurs (McBride & Wuebker, 2022; Davidsson, 2022), offering notable opportunities to various kind of entrepreneurs (Dogru et al., 2020a) and suggesting a positive effect for the host-community, on the other hand a consistent body of research has putted emphasis on the negative consequences for local residents. Starting from Guttentag (2015) and Zervas et al., (2017), two main bodies of research emerged, on the one side focusing on the disruption of Airbnb on traditional service providers' operations (Zervas et al., 2017; Farronato & Fradkin, 2022; Li & Srinivasan, 2019), and, on the other side, studying the effects of Airbnb diffusion within cities (Barron et al., 2021; Garcia-Lopez et al., 2020; Chen et al., 2022a).

[67] This is particularly important for our case study, assessing the effects of Airbnb entry on the entrepreneurial activity within marginal (rural) destinations (i.e., the Italian Borghi). These areas, although they embody a relevant touristic potential as long as they host natural or historical amenities particularly valued by tourists (e.g., lakes, castles, etc.), are, indeed, characterized by the presence of significantly higher startup costs for traditional hospitality services (which are also mainly sunk and particularly risky given the declining economic outlook). To this end, by offering its services in such destinations, the platform results in a significant reduction of supply entry costs as long as no initial investments are required to start a hospitality service.

Under the competition point of view, literature has provided concurrent findings, with Zervas et al. (2017) and Farronato & Fradkin (2022) who show different points of view on the relationship between home-sharing and hotels. Indeed, while the first contribution of Zervas et al., (2017) has pointed out Airbnb and hotels as substitute, with larger effects on lower-end hotels. On the other side Farronato & Fradkin (2022) show that the two services can act as complementor, especially when touristic peaks are likely to be reached and the flexibility of Airbnb can expand supply, decreasing prices and, consequently, increasing consumer welfare, thus shedding a light upon the positive effects of Airbnb on consumers.

Conversely to the findings of Farronato & Fradkin (2022), a large body of literature, rapidly increasing over the last years, has consistently shown that Airbnb is producing negative externalities in cities (Barron et al., 2021; Garcia-Lopez et al., 2020; Chen et al., 2022a). Indeed, studying the relationship between Airbnb and long-term rentals (LTR) researchers provided a plethora of empirical findings across different markets and with different empirical methods (Garcia-Lopez et al., 2020; Barron et al., 2021; Chen et al., 2022a) confirming the positive causal effect of home-sharing on housing rental/purchase sales, which is mainly caused by a decline of LTR supply, switched toward the short-term rental market (Chen et al., 2022a). In the same manner, the urban geography literature recognized these effects inside the city context highlighting how Airbnb is enhancing local residents' displacement processes and gentrification ones by increasing the rent gap between potential and real returns (Wachsmuth & Weisler, 2018). Finally, Carrasco-Farrè et al. (2022), by the means of a stakeholder perspective, closed the circle, highlighting how within the city of Barcelona, Airbnb closely resembles the proposition of traditional hotels, thus enlarging phenomena of increasing inequality and over-tourism.

According to the scientific literature, it results that the negative externalities (i.e., substitution with long-standing incumbents, residential displacement) of the platform are way larger than the positive ones (increases in consumer welfare, novel opportunities for multiple hosts). However, even though multiple studies have been conducted, the contexts analyzed have been homogeneous, being the empirical applications mainly focused on urban, and already economically developed, contexts. For instance, referring, Garcia-Lopez et al., (2020) analyzed the effects of home-sharing on LTR in the city of Barcelona, and Barron et al., (2021) did the same in top US cities. On the other hand, studying the effects of digital platforms on entrepreneurial activity, Burtch et al., (2018) assessed the impact of Uber roll-out in main US cities too. To this end, the lack of contributions in marginal economic areas, where opposite effects on society and entrepreneurial activity can be expected (Davidsson, 2015), clarifies the novelty and the relevance of the study.

4.2.3 The contribution of this work: home-sharing platforms, entrepreneurship, and marginal economic areas

In line with the two streams of literature discussed above, this study contributes in two ways to the ongoing scientific debate.

First, adopting the perspective through which the platform can act as *External Enabler* of entrepreneurial opportunities (Davidsson et al., 2015), this chapter contends that, as opposed to the effects clearly depicted in cities, the widespread diffusion of digital platforms in marginal economic areas can have opposite effects. On the one side, indeed, the entry of platform within cities acts as deterrent as it increases opportunity costs to pursue entrepreneurial activities (Burch et al.,

2018; Acs & Armington, 2006; Block & Koellinger, 2009) by proposing itself as a viable alternative to the multiple opportunities that a city already offers (Glaeser et al., 1992; Duranton & Puga, 2004). On the other side, as long as the local market in marginal areas does not propose any viable alternative, prospective entrepreneurs can take advantage of the supply/demand shock caused by the platform to gather either the opportunities provided by the technological advancements of platforms (McIntyre & Srinivasan, 2017) or the potential greater profit opportunities (Parker et al., 2016). In this sense, this study conveys that the platform acting in marginal economic areas results in an *External Enabler* (Davidsson, 2015), rather than an increasing opportunity cost for prospective entrepreneurs.

Second, referring to the case of home-sharing platforms, the presence of these multiple theoretical arguments, and a vary and relevant backbone of research findings (Garcia-Lopez, 2020; Barron et al., 2021; Chen et al., 2022a; Farronato & Fradkin, 2022; Zervas et al., 2017), reveals the relevance of this study. On the one hand, indeed, there are reasons to think that the penetration of such platforms within the economic texture (of the city) can go out of control, thus revealing negative side-effects hurting residents (Chen et al., 2022a; Carrasco-Farrè et al., 2022) or traditional incumbents (Zervas et al., 2017). On the other hand, under the points of view of the *External Enabler* in marginal economic conditions (Davidsson, 2015), home-sharing platforms can act as endogenous economic growth mechanisms, helping entrepreneurs that are struggling to carry on their ventures as they face unfavorable economic conditions, and policy makers willing to increase the economic conditions of marginal destinations. In this sense, this research can provide a novel point of view on the long-debated home-sharing platform Airbnb, adding further elements to the discussion on whether and when the platform has positive or negative effects, thus envisaging relevant policy implications for local governments. In this rationale, this chapter hypothesizes that when diffusing within the marginal economic market, the online platform generates effects spanning well beyond the reference sector, thus enabling opportunities in closer sector too.

From a methodological point of view, this study bridges both highlighted literature streams also under the methodological point of view. Indeed, despite the aim of this analysis is not to show whether and how Airbnb can compete with traditional incumbents or raise LTR prices, specific methods are also drawn upon both streams of literature, as long as they provide both the instruments to deal with entrepreneurship and short-term rentals. In particular, similarly to Burtch et al., (2018), this study takes advantage of asymmetric entry of Airbnb within each analyzed local market, thus proposing a quasi-experimental study (DID with staggered treatment) which differs from the approaches of Barron et al., (2021) or Garcia-Lopez et al., (2020). Complementarily, the latter studies provide methodological advancements to design additional identification studies, leveraging on the differential exposure of individuals (cities, neighborhoods, etc., in our case the Italian Borghi, see Section 3) to the diffusion of Airbnb.

4.3. Empirical Setting: The Italian Borghi

The analysis is confined to a specific context, the Italian Borghi. According to the Italian Ministry for Culture, an Italian Borgo is defined as a "*small town, or an aggregation of small municipalities, with a small living population in which an*

historical borgo has to be clearly identifiable and visible. In case of very small Borghi, the historical part can constitute the whole municipality"[68]. In line with this definition, the Italian Borghi are small towns (an average Borgo is about 51 squared kilometers large) with few inhabitants (on average, less than 4,000 inhabitants per Borgo), typically collocated within rural areas (in 77% of the cases, i.e., areas with very low population density) or areas with intermediate population density (in 23% of the cases)[69]. The economic texture of the Italian Borghi is characterized by the strong presence of entrepreneurs running small ventures as almost the total enterprises active within a Borgo are based on simple associations or partnerships, while the main activities carried on in these markets are mainly related to the touristic vocation of these areas such as: restoration, primary sector (e.g., agriculture or fishing), trade and transportation.

Despite the relevant touristic potential (see, among the others, several press-released articles from famous magazines in the footnote[70]) embodied in the presence of unique historical amenities (e.g., the historical center or the presence museums) or attractive natural ones (e.g., lakes), and the novel post-Pandemic touristic trends that are putting rural destination at the forefront of tourists' choices (Zoğal et al., 2022), the current and prospective socio-economic landscape of the Italian Borghi is not flourishing being many indicators declining over time. For instance, taking as approximation the presence of young (0-14 year old) individuals, which represents the prospective and sustainable growth of a location, this indicator is significantly decreasing within the Italian Borghi, being about 9% lower comparing 2019 with 2009, while in cities it has shown an average constant pattern over time. If on the one side this decline can be attributable to multiple causes, such as for instance the increasing urbanization and growth trends of cities, as opposed to the pauperization of rural areas, on the other side, with particular reference to the case of the Borghi, a large part of their declining economic conditions is due to supply-side inefficiencies, being the traditional hospitality offer not sufficient to attract an adequate number of visitors (to this extent, it is worth to notice that an average borgo counts 0.08 hotel beds per inhabitants).

Grounding on these market conditions, this study contends that the entry of the home-sharing platform Airbnb, leveraging on the flexibility of its business model (i.e., it is able to easily reach, with lower entry costs, these rural destinations) as opposed to traditional hotels whose entry is discouraged by significantly higher startup costs, mainly sunk, can fill the supply gap, attracting demand, which endogenously creates, in turn, novel opportunities for entrepreneurs within different industrial sectors.

[68] In a latest call for application for funded projects aimed at restoring a selection of 250 *Italian Borghi*, a stricter constraint on the population is required to be classified as *Borgo*, being it 5.000 inhabitants at most. However, for the purpose of the analysis, we will rely on the list of the *Italian Borghi* provided by the officially recognized association *I Borghi più Belli d'Italia* (https://borghipiubelliditalia.it/borghi/), as described in section 4.1.

[69] The statistics in this section (i.e., section 4.3.) refer to the sample of Borghi as explained in section 4.4.

[70] Article #1, CNN (2022): https://edition.cnn.com/travel/article/most-beautiful-villages-italy/index.html
Article #2, Il Sole 24 Ore (2020): https://www.ilsole24ore.com/art/recuperare-borghi-d-italia-puo-valere-2-miliardi-ADq10Dm

4.4. Data & Methods

4.4.1. Data Description

The analyses are based on a unique and novel database which merges information from different sources. The data are organized with a panel structure containing yearly information of 270 Italian Borghi (those recognized from the association I Borghi più Belli d'Italia, the full list is accessible here: https://borghipiubelliditalia.it/borghi/, that are compatible with the definition of the Italian Ministry for Culture, see section 4.3.) from 2009 to 2019.

Per each borgo the following variables have been measured. First, according to AirDNA data (www.airdna.co), per each year, from 2009 to 2019, the number of active Airbnb in a Borgo has been measured, such that consequently it has been able to identify Borghi who experienced the entry of the platform (i.e., those registering at least one Airbnb) and the timing at which the platform entered the Borgo (i.e., the year in which the first Airbnb opened in a given Borgo). Second, additional information about the entrepreneurial activity has been retrieved from multiple sources. In line with Burtch et al. (2018) this study takes advantage, as main approximation of entrepreneurial activity in a Borgo at a given year, data coming from the official declaration of income (derived from the Italian Ministry for Finance[71]), thus measuring the total Borgo-level income from entrepreneurial activity and the per capita one (furthermore, additional information about other types of income, such as employee income and income by classes, which are useful to compute income equality distribution metrics, have been gathered)[72]. Furthermore, to the extent of providing novel findings to the literature, novel sector level data, coming from the Italian Chamber of Commerce[73], containing the number of active firms in a given Borgo at a specific year (from 2009 to 2019) by industrial sectors (namely the first letter of the Italian ATECO classification, see https://codiceateco.it) as well as the overall total number of firms have been used. Finally, the main socio-economic variables including the municipal level number of hotel beds (time-varying), the provincial GDP and unemployment rates, as well as population measures, which are indicator depicting the socio-economic status of each borgo, have been derived from the official Italian Center for Statistics, ISTAT (https://www.istat.it).

This study excludes 2020 from the analyses (even if data from the income declarations and from the Chamber of Commerce are already available) because the aim of the analysis is to estimate the impact of a platform entry on local entrepreneurial activity in a standard economic situation, such that the shock caused by Pandemic outbreak may invalidate the presence of statistically significant relationships. However, as discussed in the conclusions, important implications from the study for the post-Covid touristic industry may be derived, given the increasing importance of rural destinations as relevant asset for the tourism recovery within the Italian country.

[71] Data are accessible here: https://www1.finanze.gov.it/finanze/pagina_dichiarazioni/public/dichiarazioni.php
[72] It is worth to notice that in Italy there are both *Ordinary* and *Simple* entrepreneurs depending on the typology of the firm they hold (e.g., limited liability for the first kind of entrepreneurs, or associations/partnerships for the second kind). The variable used in the paper is a composite metric, summing both types of income declared by the two types of entrepreneurs.
[73] Website link is accessible here: https://www.registroimprese.it

4.4.1. Identification Strategy: Econometric Approach

The aim of the research is to test whether the entry (and the subsequent diffusion) of Airbnb into the context of a Borgo fosters the local entrepreneurial activity. However, it is unlikely that Airbnb randomly enters Borghi (namely hosts decide to put their spare space on the short-term rental platform, joining Airbnb) because distinct features of the borgo (e.g., size, the presence of natural attractions) may make it an attractive feature for potential Airbnb hosts while also affecting the presence of entrepreneurs. This results into endogeneity problem: in other words, biases in the analysis are likely to emerge without properly dealing with the presence of omitted variables and the absence of randomized treated group selection (i.e., random Airbnb entry assignment to the Borghi within our datasets). To this extent, this chapters proposes the following econometric specification aimed at tackling the endogeneity issues arising within the estimation procedures. First, in all econometric models include Borgo-specific fixed effect which control for any time-invariant unobserved (and observed) characteristics which may be correlated with both the entry of Airbnb and the entrepreneurial activity. Second, they include time and state (NUTS2) by time fixed effects to account for time-varying shocks common to all Borghi and shocks either at the national-year or at the regional-year level. Third, time-and-individual varying controls variables the are likely to be correlated with both Airbnb and entrepreneurial activity such as the provincial GDP and unemployment and the number of hotel beds at the borgo level (which is likely to discourage/encourage the entry of Airbnb while surely positively affecting the entrepreneurial activity within the city) have been added. It is worth to notice that the inclusion of the provincial GDP and unemployment rate, to the extent that they are strongly correlated with Airbnb diffusion (Dogru et al., 2020b), allow the empirical model to control for the local diffusion of Airbnb within the same province, which can result in spatial spillover effects on the entrepreneurial activity within the Borgo.

Fourth, and most importantly, the empirical approach is designed as quasi-natural experiment because it exploits the fact that Airbnb enters in different subsamples of Borghi at different point in time and not all Borghi within those analyzed have seen the entry of the short-term rental platform, thus providing a valid control group (i.e., the Borghi belonging to the official list who have not seen the entry of Airbnb between 2009 to 2019) as opposed to a treated one. To this extent, the main specifications of the research adopt the *Panel Data Event Study* approach (Clarke & Tapia-Schynte, 2022), or in the sense of Angrist & Pischke (2008), a relative time model, which allow to estimate the causal impact of Airbnb entry on local entrepreneurial activities at different point in time before and after treatment assignment.

This model specification is a generalization of the traditional difference-in-difference (DID) model with two-way fixed effects (i.e., individual and time ones). In particular, while in the traditional DID model, treated units are treated simultaneously, in this empirical setting, treated units (i.e., Borghi who faced the entry of Airbnb) are treated at multiple points in time (i.e., Airbnb enters Borghi in different years, varying from 2009 to 2015), such that we have a staggered treatment (Gao & Zhang, 2017). To the extent that the treatment is observed at multiple points in time, the Panel Data Event study approach is particularly useful, because it aligns multiple treatment timing on a common time-axis, where 0 equals to the treatment assignment period (i.e., Airbnb enters a specific Borgo), periods starting from -1 to the beginning of the sample

are respectively "one year before treatment", "two years before treatment", and so on, while periods from +1 to the end of the sample period are respectively "one year after treatment", "two years after treatment" and so on (see for a similar estimation technique Gao & Zhang, 2017, who estimated the effects of employment non-discrimination acts on corporate innovation, or, closely tied with the scope of this paper, Burtch et al., 2018, who estimated the effects of Uber entry in main US cities on local entrepreneurial activity).

[Insert Table 4.1. here.]

Table 4.1. shows the share of entries of Airbnb within the 270 Italian Borghi. In total, 71 Italian Borghi (26.30%) have never seen, within our timespan, the entry of Airbnb, thus they are collocated within the control group. The majority of the Borghi who have seen the entry of Airbnb received the treatment between 2011 and 2013 (about 56% of the total). It is worth to notice that the control group we have chosen for the analysis particularly fits with the purpose of the study as both treated as sample units are drawn from an *official* list of Italian Borghi, whose definition is strictly defined by the Italian Ministry of Culture, thus, after controlling for individual fixed effects, and cross-sectional time varying variables, it is plausible to conservatively assume that treated and control group are effectively comparable.

The main estimated equation, in line with Clarke & Tapia-Schynte (2022) or Angrist & Pischke (2008) is as follows, in Equation 4.1:

$$\ln Y_{i,t} = \alpha + \sum_{j=t-K_i}^{j=E_i-1} \beta_j * Lag_{i,j} + \sum_{j=E_i}^{j=M_i} \gamma_j * Lead_{i,j} + X_{i,t} + \tau + \eta + \varepsilon_{i,t}$$

(Eq. 4.1 – Panel Event Study Equation)

Where $Y_{i,t}$ is the dependent variable. According to the data at disposition, firstly multiple dependent variables approximating the overall entrepreneurial activity within the borgo have been tested. These are: a) $INCOME_{i,t}$ that is the total income from entrepreneurial activity in a Borgo *i* at year *t* derived from , b) $INCOMEpc_{i,t}$ that is the per-capita income from entrepreneurial activity in a Borgo *i* at year *t*, c) $FIRMS_{i,t}$ that is the number of active firms across all industrial sectors in a Borgo *i* at year *t*. All variables have been log-transformed before being included into the model. Second, to the extent of providing a more precise picture of the effects of Airbnb on the local entrepreneurial activity, an alternative set of dependent variables, including the number of active firms in nine different industrial sectors: primary sector (i.e., agriculture, fishing), secondary sector (i.e., manufacturing), trade, transportation, hospitality (i.e., restaurants and traditional accommodation), financial services, real estate, travel agencies and services supporting firms, and entertainment have been tested. Those industrial sectors have been chosen because they represent the majority of the sectors which can be working in a market such as a Borgo. As reported in Appendix A4.1 Panel A, on average, these sectors account for about the 80% of the active firms in our markets, with these means being not different between treatment and control groups and between before and after treatment periods. Furthermore, for the sake of completeness, Appendix A4.1 Panel B reports the sub-sectors working within each of the industries analyzed.

$Lag_{i,j}$ is a set of dummy variables indicating the years before the treatment starting from T-1 (one year before the treatment) to the first available data at our disposition. In line with this structure, the coefficient β_j are an indication of eventual pre-treatment effects. $Lead_{i,t}$ is a set of dummy variables indicating the year after the treatment, starting from T=0 (when the treatment has been assigned) to the last available information. To this extent, the coefficients γ_j are those reporting the average treatment effect 0, 1, 2, and so on, years after the treatment assignment.

$X_{i,t}$ is a set of control variables, which control for the presence of individual/group-time varying omitted variables that are likely to affect either the dependent variable or the treatment assignment (i.e., entry of Airbnb). In particular, $X_{i,t}$ contains: a) the number of hotel beds in the Borgo *i* in a given year *t* (log transformed), which is a crucial control variable because the entry of Airbnb may attract the entry of traditional players, thus overestimating the average treatment effect in Eq. 4.1., the yearly unemployment rate in the province where the Borgo is located, the yearly provincial GDP where the Borgo is located (log transformed), and a region (NUTS2) by year fixed effects which account for any yearly shock at the regional level (e.g., natural occurrences or any other omitted events, or legislations, which are likely to affect both the presence of Airbnb and the local entrepreneurial activity). τ and η are respectively time and individual (Borgo) fixed effect which are crucial to control for any time-varying and cross-section varying omitted variables.

It is worth to notice that, in order to interpret leads and lags according to a no/pre-treatment period, the dummy variable indicating one year before the treatment (T-1) has been omitted (as often done in literature, see Chen et al., 2022, for an application of relative time model applied to Airbnb case). To this extent, any leads and lags must be interpreted as compared to the year before the treatment assignment. Furthermore, in line with the distribution of Airbnb entries within the Borghi population (see Table 4.1.), all lags from T-2 (two years before the treatment) to the first available lags have been grouped together. Similarly, all effects starting from T+4 (four years after the treatment assignment to the latest data) have been grouped into a single dummy.

To the extent of providing evidence on the robustness of our results, highlighting the evidence of *causal* effect on entrepreneurial activity, a large battery of robustness checks will be provided, namely testing the validity of the evidence with regards to pre-treatment trends and the presence of spurious effects by the means of different placebo falsification tests, an exposure-design IV approach (Bartik, 1993; Goldsmith-Pinkham et al., 2020; Cowgill et al., 2022), which accounts for potential endogeneity of the treatment due to unobservables (Borgo-time varying) not accounted in Eq. 4.1., and a Coarsened Exact Matching (CEM) procedure (Blackwell et al., 2009).

[Insert Table 4.2. here]

Table 4.2. provides the descriptive statistics of the variables employed in the econometric analyses as well as a brief description and the respective sources. The average values confirm that the markets analyzed in this research are very small, being characterized by an average number of active firms equals to about 400 (median 264). In line with the economic texture of the Borghi, the main developed industries are primary sector (i.e., agriculture of fishing), trade and

hospitality (i.e., restaurants and traditional accommodation services), with respective mean values of 115, 87 and 32 active firms per year per Borgo.

4.5. Results

4.5.1. Global Entrepreneurial Activity

Table 4.3. shows the estimation for the three dependent variables indicating the entrepreneurial activity in a specific borgo. All models adopt bootstrapped standard errors (and results have been confirmed with traditional standard errors), and, according to Eq. 4.1., all models control for the set of control variables $X_{i,t}$, and the two-way fixed effects. For the sake of completeness, Figure 4.1. shows the plot of the treatment effect for the three dependent variables including the 90% confidence intervals.

[Insert Table 4.3. here.]

[Insert Figure 4.1. here.]

The analyses show that, in general, a significant effect of Airbnb on local entrepreneurial activity exists. However, this effect is not immediate, as it tipically takes about two to three years to become statistically significant, and, furthermore, it is increasing in the years following the treatment assignment. An interpretation of this result refers to the presence of multiple effects acting together. On the one side, it is likely that a critical mass effect is present, in the sense that local entrepreneurs perceive the effects of Airbnb only when a sufficient diffusion of the platform's producers (i.e., Airbnb listings) has been reached. On the other side, it is plausible that these processes have a natural *adjustment* timing, such that following the shock (i.e., the entry of Airbnb), entrepreneurs first, have to perceive the signal of new/increasing market opportunities, then they have to prepare their businesses to be able to compete in the local market and finally they arrive on the market. Indeed, immediately following the entry of Airbnb in an average borgo, no significant effects on the total income from entrepreneurial activity is found, while four years after the treatment, the models notice a +23.6% compared to an "untreated" counterfactual. Since the global revenues are a composite metric, jointly considering either "scale" (increase in the number of firms generating income) effects and the "creation of value" (increase in the unit level income), the analyses have separately estimated the effects on the per capita income from entrepreneurial activities and on the total number of firms that are both representative of the entrepreneurial activity but distinguish between the two kinds of effects. Both effects are likely to act. In particular, it is worth to notice that in the long run (4 years after the Airbnb opening), per capita income from entrepreneurial activity is likely to grow by +5.3% compared to an "untreated" counterfactual, similar to number of firms, which is increasing by +5.0% compared to the counterfactual.

Equivalently, in monetary terms, the results show that two years following the entry of Airbnb, in the median borgo it is possible observe an increase of 152,971€ of declared income from entrepreneurial activity, three years after an increase of 206,511€ and from T+4 onwards, this amount sharply raises up to more than 361,000€. Furthermore, in the long

run, the analyses predict that an average entrepreneur in the median borgo would increase its declared income by about 900€ annually, while the number of active firms within the Borgo would increase by more than 13 firms (which is relevant, considering the small dimensions of these markets, whose surface is on average 50 squared kilometers).

Finally, it is worth to notice, the coefficient β_j, indicating the treatment effect from two years before the treatment, is always not significant in all model specification, such that it is possible to conservatively assume that no pre-treatment effects exist, indicating that the results are robust to any pre-treatment deviations of trends. However, further econometric specification will test the robustness of our results, as reported in section 4.5.3.

4.5.1.1. Standard DID approach

For the sake of completeness, the model with the standard two-way fixed effect (TWFE) difference in difference has been tested too, thus estimating Eq. 4.2.:

$$\ln Y_{i,t} = \alpha + \lambda DID_{i,t} + X_{i,t} + \tau + \eta + \varepsilon_{i,t}$$

(Eq. 4.2. – Standard TWFE DID approach)

[Insert Table 4.4. here.]

Where $DID_{i,t}$ is a dummy variable equals to one if the observation belongs to the treated group in a post-treatment period. Compared to the panel event study approach, this estimation does not distinguish the effects according to the timing from the treatment occurrence, thus averaging the effects in the post treatment period. Results are available in Table 4.4. The Table shows that a significant effect in the case of total entrepreneurial income (*$INCOME_{i,t}$*) still exists, with treated Borghi registering a +10.4% compared to untreated ones. Second, the estimates point out that the coefficient λ is not significantly different from zero, with p-values equal to 0.127 when $Y_{i,t}$ is *$INCOMEpc_{i,t}$* and 0.108 when $Y_{i,t}$ is *$FIRMS_{i,t}$*. There are rgumenttations to think that these results do not invalidate the analyses. Indeed, the coefficient λ averages all post-treatment period, thus including both those right after the treatment assignment that are found to be not significantly impacted by Airbnb entry (see Table 4.3.) and those in the long run, such that it is likely that in a shorter panel like the one used in the paper (i.e., it has data for 10 years only) the prevalence of observations immediately after the treatment assignment can prevail and consequently make the overall treatment effect not significant. Second, the statistical significance of the coefficient is very closed to the threshold of 0.100, which suggests that an effect is very likely to hold. In other words, this additional specification confirms the validity of the event-study approach, which is able to distinguish according to the timing from treatment assignment.

4.5.1.2. Continuous Treatment approach

Since it is plausible that a scale effect is likely to exists (previous referred as critical mass effect), such that, not only the entry of the platform has an impact, but also its relative penetration, the model employing a modification of the standard

TWFE difference in difference using a continuous treatment has been additionally tested. In this case, the estimating equation is Eq. 4.3.:

$$\ln Y_{i,t} = \alpha + \lambda DID_{i,t} * \ln(\text{AirbnbPenetration}_{i,t}) + X_{i,t} + \tau + \eta + \varepsilon_{i,t}$$

(Eq. 4.3. – Continuous Treatment TWFE DID approach)

[Insert Table 4.5. here.]

Where the variable $\text{AirbnbPenetration}_{i,t}$ (computed as the ratio of Airbnbs active in a Borgo *i* at year *t* to the Borgo's surface) represents the continuous treatment. In other words, with this specification, the treatment effect is disentangled not upon the assignment or not of the treatment, but upon the *intensity* of it, exploiting the fact that within the Borghi who faced the entry of Airbnb (i.e., treatment group), the diffusion of the platform has been heterogeneous[74]. Results are reported in Table 4.5. The results show that per each percentage increase in the penetration of Airbnb, positive and significant impact hold for all the variables representing the global entrepreneurial activity. In particular, per each percentage increase of Airbnb penetration, the total income from entrepreneurial activity is expected to be 0.141% higher, the per-capita income from entrepreneurial activity to be 0.043% higher and the number of firms active within the Borgo to be 0.025% higher. The evidence points out that aside of the binary effect (treated vs non-treated) of Airbnb on the entrepreneurial activity, also a diffusion effect is expected to exist, such that where the diffusion of the platform is more pronounced, larger effects are expected.

4.5.2. The Mechanisms behind Value Creation: Impact by Market Sectors

To the extent of enlarging the results, Eq. 4.1 has been tested over multiple independent variables, each indicating the log of number of active firms in a Borgo belonging to nine different ATECO codes, representing the majority of the industrial sectors active in these specific markets (see Appendix A4.1). Since it is likely that the entrepreneurial activity in a specific industrial sector is strictly dependent on the presence and growth of other sectors (i.e., for instance it is likely that primary sector is more likely to emerge/growth if adjacent sectors in the value chain like hospitality/restaurants arise, and vice-versa), Eq. 4.1. has been slightly modificated by including within the set of control variables the lagged value of the total number of active firms in the given Borgo[75], which approximates the industry status one year before the examined time.

[Insert Table 4.6. here.]

[Insert Figure 4.2. here.]

[74] This modification of the difference in difference approach has flourished within the medicine literature, where the effects of differentials dose of a treatment (e.g., a specific drug) on the health status of a patient are evaluated. In recent years, given the notable insights which can derive from this specification, also economist started to apply this methodology. See for instance Angrist & Imbens (1995) or Callaway et al. (2021). In order to estimate this modification of the traditional DID, the research has taken advantage of the Stata package suitable for DID estimation.

[75] However, the robustness of the results has been also tested on the same econometric specification as in Eq. 4.1., with no significant differences to those reported in the main text. Results are available in Appendix A4.2.

Table 4.6. provides the results, while Figure 4.2. shows the event study plots per each of the industrial sectors studied. Two sources of variation within market sectors are identifiable, namely: the significance/magnitude of the impact of Airbnb entry and the respective timing for the effects to become significant.

In particular, first it is possible to notice that, neither in the short or in the long run, trade and financial services sector have registered a significant increase in the activities due to Airbnb entry, suggesting that these activities are typically externalized out of the borders of the Borgo (or carried out by firms located out of the Borgo context). On the other side, all other sectors, which are closely tied to the economic texture of the Borghi (normally devoted to tourism, artisanship, and primary activities), have benefited from the platform diffusion within the local market, with different magnitudes and timing of the impact. Among the others, closely tied with tourism related activities, firms active within entertainment services are in the long run (i.e., from T+4 onwards) 11.5% higher compared to untreated counterfactual, those within transportation services are 10.8% higher, those in hospitality services (including food activities such as restaurants or farmhouses) are 8.6% higher, those in support services (such as rentals and travel agencies) are 7.9% higher and, finally, firms within real-estate services are 10.8% higher. This evidence suggests that Airbnb, by entering the local market, has a clear footprint on all the activities directly linked to the touristic value chain. In particular, to the extent that Airbnb is able to stimulate touristic demand by generating touristic flows in these markets, the research contends that the effects generate positive externalities over local the local industry, translating the demand for touristic services to demand for adjacent and similar services. This evidence is even more important if it is considered that, if on the one side it is plausible that Airbnb can capture the majority of the value within the segment of hospitality services (in the strict sense of overnight stay services) and bring these profits out of the Borgo, on the other side the spillover effects generated on the adjacent sectors by the means of a wider market exposure to novel consumer demand, can generate additional income which are more likely to remain within the Borgo, fulfilling its economic growth (as also confirmed by the global effect on the total declared incomes from entrepreneurial activity in section 4.5.1.). These effects are in the long run even more important, considering that also industrial sectors that are typically collocated in the upstream positions of the value chain, such as primary (i.e., agriculture or fishing) and secondary (i.e., manufacturing) sectors are stimulated by the entry of the platform, registering respectively +4.3% active firms for primary industry and +7.7% active firms for manufacturing from T+4 onwards. In this sense, the analyses argue that this effect is a combination of multiple ones, belonging to the platform and to the effects on other parts of the value chain (e.g., it is plausible, indeed, that Airbnb by stimulating restaurants has increased the demand for food services which have increased the demand for raw materials, stimulating the entry of entrepreneurs in the primary sector), confirming the validity of the additional control variable $FIRMS_{i,t-1}$.

The differential timing for the effects to become significant provides additional insights to the mechanism of value creation generate by Airbnb within the Borghi. Consistently with the former explanation, the results acknowledge that the first industrial sectors being stimulated by the entry of Airbnb are transportation, hospitality, and entertainment, which register a significant increase in their entrepreneurial activity starting from one year following the entry of the platform. Then, starting from the long run only, other sectors such as travel agencies and support services, or primary and secondary

sectors are being affects, confirming the market mechanisms previously highlighted such that value creation first starts from downstream services and then goes upstream within the value chain.

4.5.3. Robustness Checks

To the extent that designing a difference-in-difference methodology requires multiple assumptions which are at the basis of the validity of the estimates (Clarke & Tapia-Schynte, 2022; Angrist & Pischke, 2008), multiple robustness checks have been fulfilled to relax the main assumptions or further confirm them. For this reason, this section shows the results of a) two placebo-falsification tests, b) an instrumental variables approach which argues that the treatment is endogenous, and c) a Coarsened Exact Matching (CEM) which aims to minimize the differences between treated and control units.

4.5.3.1. Placebo-Falsification Tests

Two main placebo-falsification tests have been conducted to further confirm the validity of the empirical approach. The aim is to test the robustness of results according to: a) the existence of pre-treatment trends which would invalidate the main assumption behind the selected DID model (tested in Placebo-Falsification #1), and b) the fact that the coefficient indicating the *causal* effect of Airbnb on local entrepreneurial activity is somewhat random and not representative of the effects generated by the platform entry into the local market (tested in Placebo-Falsification #2).

4.5.3.1a. Placebo-Falsification #1 – Robustness to pre-treatment trends

In order to test whether results are robust to the presence of pre-treatment trends (which would invalidate our results), the following placebo-lead test has been constructed. First, only those observations belonging to the treated group, still in the pre-treatment phase only, or to the control group (all observations within the dataset) have been selected. Second, the treatment has been re-assigned in a random year to all the treated units within the sample. To this extent, it is worth to notice that the random assignment can happened between the starting year of the panel (i.e., 2009) and one year before the real treatment occurrence in a given treated borgo *i*. Third, this random assignment has been replicated per 1,000 times, storing per each time the regression coefficients, as well as the p-values indicating the statistical significance of the random treatment assignment effect on the local entrepreneurial activity. To the extent that according to this simulation the temporal length of the panel is significantly shorten, the simulated placebo effect is tested on two econometric specifications: a) a panel event study approach, as in Eq. 4.1, where all pre "random-placebo" treatment effects from T-2 backwards (as in the main specification) are accumulated in single dummy, as well as all post "random-placebo" treatment effects from T+1 onwards; b) a standard TWFE DID with all the control variables as in Eq. 4.2.

[Insert Table 4.7. here.]

Table 4.7. shows the distribution of the p-values of the variables T0 and T+1 from a panel event study approach, and of $DID_{i,t}$ from the standard TWFE DID approach. The Table shows that per each of the three dependent variables representing the overall entrepreneurial activity, the level of statistical significance of the post-treatment effects is well above the acceptance threshold of 0.100. On average, it is shown that, based on the 1,000 random allocations, the average p-

value of T0 varies from 0.339 (for $Y_{i,t}$ = $FIRMS_{i,t}$) to 0.617 (for $Y_{i,t}$ = $INCOMEpc_{i,t}$), the average p-value for T+1 onwards varies from 0.464 (for $Y_{i,t}$ = $FIRMS_{i,t}$) to 0.577 (for $Y_{i,t}$ = $INCOME_{i,t}$) and the average p-value for $DID_{i,t}$ varies from 0.458 (for $Y_{i,t}$ = $INCOME_{i,t}$) to 0.613 (for $Y_{i,t}$ = $FIRMS_{i,t}$). Alternatively, as additional explanation, Appendix A4.3 shows the distributions of the p-values of T0, T+1 onwards and $DID_{i,t}$ for the dependent variable $INCOME_{i,t}$[76].

Based on this evidence, it is possible to conservatively confirm that the parallel trend assumption holds within the data. In other words, the analyses can conservatively assume that no anticipation effects exist, confirming the validity of the experimental DID event study approach.

4.5.3.1b. Placebo-Falsification #2 – Robustness to spurious correlations

Despite Placebo-Falsification test #1 provides a robust indication of the fact that pre-treatment trend is not present within data, it could be the case that the results displayed within the main models (see Tables 4.3. and 4.6.) are not driven by Airbnb, but by some random factors, relative to the specified control group. In order to test if the estimates are robust to these spurious effects, such that the effects are effectively driven by Airbnb entry, the following placebo tests involving the control group only (taking inspiration from Chen et al., 2022) has been designed. In particular, first the sub-sample of the data containing only control group observations has been selected. Then, the treatment has been randomly assigned to 50% of the selected sub-sample at a random timing (i.e., between 2009 and 2019). As for Placebo-Falsification #1, this random allocation has been repeated per 1,000 times, storing per each time the coefficients and the p-values indicating the average treatment effects either in the case of panel event study approach or standard TWFE DID approach. If those unit do not show a significant impact of Airbnb on their local entrepreneurial activities, then the estimated coefficients for the average treatment effects must be not statistically significant. Differently from Placebo #1, since the full temporal length of the panel at disposition is available, the panel event study approach has been tested as reported in Eq. 4.1.

[Insert Table 4.8. here]

Table 4.8. shows the distribution of the p-values from 1,000 random allocations of treatment to units belonging to the control group. Coefficients from T0 to T+4 onwards are from a panel event study approach, while the coefficient of DID is from a standard TWFE DID approach. The Table shows that on average, the level of statistical significance of the treatment effect is well above the threshold of 0.100, being it varying between 0.297 (T+4o for $Y_{i,t}$ = $FIRMS_{i,t}$) and 0,733 (T0 for $Y_{i,t}$ = $INCOME_{i,t}$). To this extent, it is possible to conservatively confirm that on average a random treatment allocation to units belonging to the control unit has no significant effect on the outcome variables (i.e., local entrepreneurial activity), such that, the main results are not effectively driven by random factors or spurious correlation, still can be directly attributable to the entry of the platform into the local market (i.e., the treatment).

[76] Additional charts are available upon request to the author.

4.5.3.2. Instrumental Variable Approach – Exposure Design

Although the former robustness checks confirm the correct implementation of the panel event study methods estimating the impact of Airbnb on local entrepreneurial activity, this sub-section further relaxes the assumption of treatment exogeneity (after controlling for individual and time fixed effects, and local economy control variables) implementing an exposure-design IV approach (Cowgill et al., 2022; Goldsmith-Pinkham et al., 2020). The causes of potential endogeneity within our Eq. 4.1. can rely on the presence of omitted variables at the Borgo-Year level, such as the presence of regulations or borgo-specific initiative aimed at fostering the touristic attractiveness of the local market. The main idea behind this IV design is that each unit (i.e., a Borgo) is differently exposed to the shocks (i.e., Airbnb entry), with the exposure varying both cross-sectionally and across time (see the seminal paper discussing this methodology from Bartik, 1993).

The corresponding instrumental variable has been implemented in line with the main empirical literature employing Bartik-like instruments (Bartik, 1993). Among the others, this method follows Garcia-Lopez et al., (2020) or Barron et al., (2021) who applied this differential exposure design approach to study the impact of Airbnb penetration on long-term rentals within the city of Barcelona or in the United States. To the extent that the observational unit of the panel is Borgo-Year, the proposed instrument is composed as the product of two terms, one varying across individuals (called *share* component) and the other one varying within time (*shift* component). First, in line with the main theories on new product diffusion (Bass, 1969) it is plausible that a Borgo is differently exposed to the entry of Airbnb as the platform's popularity gets to increase. In this sense, there exists an information effect, which is varying only across time (while is common to all Borghi) and is likely to incentivize the decision to join Airbnb. To this end, in line with Garcia-Lopez et al., (2020) and Barron et al., (2021), this analysis proxies this term using the nation-wide (i.e., Italian) queries on Google for "Airbnb". This variable has the further advantage of being normalized across time within our time interval (2009-2019) on the scale 0-100. Second, regarding the cross-sectional component, it is likely that a Borgo is more exposed to the entry of the platform as the presence of Airbnb-style amenities increases, as long as an increasing number of them is likely to increase the incentive to a prospective host to join platform (i.e., the higher the presence of Airbnb style dwellings within the Borgo, the higher the incentive because lower capital investments are required to entry the platform). In this sense, the proposed cross-sectional component approximates the share component as the total number of residential dwellings in the Borgo (derived from ISTAT National census in 2011[77]). Finally, the proposed instrument is thus composed as the product of the Google search queries multiplied by the log of the residential dwellings.

A traditional 2SLS approach has then been applied, first estimating the treatment assignment, and second using either the predicted treatment into Eq. 1, or a control function approach (Petrin & Train, 2010). In the first stage, to the extent that the treatment is binary, a logistic regression, employing the same set of control variables, has been adopted to

[77] Although 2011 is before the first entry of Airbnb in Italy, it is possible to conservatively assume that this value has been slightly influenced by the diffusion of Airbnb. Indeed, among the sample, only a quarter of the Borghi has been treated up to 2011, still with very low values of penetration.

predict the probability that a Borgo *i* at a given period *t* is treated or not. In this sense, the first stage estimated the variable $DID_{i,t}$ (present in Eq. 4.2.) to be equal to one or not. The results of first stage equations have been used in two, alternative, ways. In the first case, the predicted probabilities have been computed and by the means of cut-off threshold equals to 0.75 it has been estimated whether a Borgo is treated at a specific time (i.e., if $Pr[DID_{i,t}]^{estimated} >= 0.75$)[78]. By contrary, in the second case, the residuals from the first stage have been computed, and, consequently, they have been included in the main equation (Eq. 4.1.), thus employing a control function approach (Petrin & Train, 2010). Finally, the second stage of the model has been estimated using bootstrapped standard errors. Appendix A4.4. provides the first stage results, showing that the proposed IV is a significant predictor of treatment allocation positively affecting its likelihood (consistent with the theoretical argumentations as long as the instrument is the product of information effects and tracks Borghi where higher incentives to join Airbnb are available to potential hosts, which have both a positive impact on Airbnb diffusion).

[Insert Table 4.9a. here]

[Insert Table 4.9b. here]

Tables 4.9a. and 4.9b. show the results of the second stage, respectively showing a) the results using predicted treatment allocation, and b) the results using a linear and quadratic control function (Petrin & Train, 2010). In general results are qualitatively similar to those reported into the main estimates. In particular, the 2SLS estimates confirm that the effects are increasing in magnitude over time from treatment exposure. In Table 4.9a., only the treatment effect at T+4 is found not to be significant for $Y_{i,t} = INCOME_{i,t}$. Although the p-value is closed to the threshold of 0.100, that this can be consequence of the loss of efficiency of a 2SLS approach. Similarly, in Table 4.9b., nonsignificant effects are found for $Y_{i,t} = FIRMS_{i,t}$, although the variable is significantly impacted by Airbnb diffusion in Table 4.9a. In this sense, it is worth to notice that the first stage typically underestimates probabilities around real treatment allocation, thus shortening the length of the observation following the treatment.

4.5.3.3. Coarsened Exact Matching Approach (CEM)

Finally, as often done in empirical applications adopting DID and its variations (Chen et al., 2022; Burtch et al., 2018), the robustness of the results has been also used adopting a matching procedure. Matching methods allow to construct a specific control group by matching each treated individual with not treated ones according to multiple variables, in order to ensure that within the DID application, treatment and control group are as comparable as possible (Blackwell et al., 2009).

In this robustness check the methodology proposed by Blackwell et al., (2009), employing a Coarsened Exact Matching (CEM), has been strictly followed. In particular, first, the variables upon which building the matching procedure has been

[78] This threshold has been chosen in order to have a good trade-off between specificity and sensitivity (i.e., true negative and false negative rates).

selected. To this extent, Borghi have been matched according to a) the total income declared within a Borgo (which is a representation of the overall economic level of the individual), b) the total active population (which is a representation of the *size* of the Borgo) and c) the total number of hotel beds (which are a strong indicator of active touristic activities within the Borgo). Matches have been performed on the distribution of these variables in 2009 (the first year of the panel), which can be intended before the entry of Airbnb (as reported in Table 1, in 2009 only 2 Borghi have seen the entry of the platform, thus being a negligible proportion of the individuals). Finally, matches have been performed by binning the three variables into five equal size bins. It is worth to notice that, as suggested by Blackwell et al., (2009), the dependent variables of the study have not been used to create matches. In total, 89% of treated individuals have been matched, and, on the other side, 94% of untreated Borghi have been matched[79].

[Insert Table 4.10. here]

The results of CEM have been then used to estimate the panel event study, and the standard TWFE DID, as reported respectively in Eq. 4.1. and Eq. 4.2. Despite the purpose of CEM is to match similar treated and control units, all control variables and time fixed effects have been still taken for various reasons. First, to the extent that bins of variables has been employed in the CEM procedure, control variables allow to interpret the treatment effect cœteris paribus the control variables, which can have a variation within the bin. Second, since control variables are both cross-sectional and time-varying, they are crucial to control for any time-varying shock. Table 4.10. shows the results of the panel event study approach, while Appendix A4.5. shows the results for the TWFE DID approach. All results are fully confirmed, with the estimated effects being slightly lower than the ones in the main estimates (as plausible expected given the procedure adopted).

4.6. Discussion and Implications

The results provide novel findings enriching the literature on digital platforms, home-sharing and their impact on local entrepreneurial activity, studying a novel context, i.e., marginal economic areas. First, as opposed to Burtch et al., (2018), this study finds that as of the entry of Airbnb in a given Borgo, the entrepreneurial activity significantly increases, with effects being increasing over time since the first platform inception and increasing according to the scale of the penetration of the home-sharing platform. The explanation of this results relies in the novel point of view of this analysis, which studies the effects of platforms in marginal/marginal contexts (Carrasco-Farrè et al., 2022), rather than in crowded and economically developed cities (Burtch et al., 2018). While, on the one side, Burtch et al., (2018) interpret the negative effects of Uber roll-out on entrepreneurial activity as consequence of increasing opportunity costs due to the presence of viable alternatives offered by platforms (Acs & Armington, 2006; Block & Koellinger, 2009), this study contends, on the other side, that these effects do exist in marginal economic areas. Indeed, if in cities (or generally, economic developed

[79] Given the larger presence of treated individuals, it is plausible that an untreated Borgo can be matched to multiple treated ones.

markets) entrepreneurs can rely their decision on strong and flourishing market conditions, enjoying the benefits of agglomeration (Glaeser et al., 1992), in marginal areas the same logic cannot be applied as long as demand and the general economic outlook in not sufficiently strong to convince entrepreneurs to embark in new ventures. In this sense, the analyses show that in markets experiencing declining economic conditions such as the Italian Borghi, still retaining several potential under-expressed remunerative assets, the global effects of a platform entry on entrepreneurial activity are positive, thus stimulating the decision of entrepreneurs to create new firms and generating positive and significant effects in the long run through all the value chain, from downward sectors to upstream ones.

According to the theoretical argumentation, the results can be interpreted in the light of a digital platform acting as External Enabler of entrepreneurial opportunities (Davidsson, 2015). In line with the main characteristics of digital platforms, that are able to easily provide a wider market exposure to forgotten areas, this paper shows that in such areas, entrepreneurs are stimulated to enter the local market as long as novel opportunities (Foss & Klein, 2020) are recognizable. In this sense, this study show that in these contexts, platforms and local entrepreneurial activity can be intended as complementors, rather than substitutes.

If this contribution is relevant to understand how entrepreneurs seize opportunities in marginal contexts when facing the entry of a digital platform, on the other hand significant elements to the debate on the effects of home-sharing to local economic welfare are provided, although the empirical analysis only analyzes the effects on income and venture creations. Indeed, following the increase of entrepreneurial activity, the estimations notice that the total income declared inside a given local market, thus concurring to the total local (Borgo-level) economic production, is likely to significantly increase. With particular reference to the case study (i.e., the Italian Borghi), a median market can experience in the long run about 361,000 € more per years declared by entrepreneurs, or, in other words, individual entrepreneurs can experience 900€ more per year (respectively 23.6% more and 5.3% more). To the extent that these incomes concur to the total income generated by the local community, thus pertaining to the marginal market, rather than to the platform, this study shows how in such conditions local policy makers have to intend platforms as endogenous growth mechanisms rather than businesses hurting the local economic welfare (as clearly expressed, in cities, by Chen et al., 2022a; Barron et al., 2021; Carrasco-Farrè et al., 2022). These results are even more important in the lights of the emerging touristic re-segmentation following the Covid-19 Pandemic. Indeed, as long as Pandemic has enhanced marginal forms of tourism (Zoğal et al., 2022), governments are acting to increase the competitiveness of marginal areas, investing relevant funds for their recovery. For instance, the Italian government proposed specific projects funded by the EU Recovery Plan in Italy aimed at supporting the recovery a selection of Borghi (https://cultura.gov.it/pnrr-borghi). In this sense, the analysis shows that complementary to exogenous fundings, endogenous actions can be taken by policy makers by collaborating with platforms, all aimed at stimulating the local economic outlook.

4.6.1. Additional Evidence for Policy Makers

Finally, given that policy makers can be interested to the global economic conditions of the local community, rather than to stimulate entrepreneurial activity only, an additional analysis, testing whether the entry of Airbnb within the Borghi

causes processes of economic inequality or residential displacements, has been constructed. In other words, this sub-section argues that rather than only stimulating the entrepreneurial process, policy makers are interested in transferring these effects on the local economic community, generating positive externalities for all inhabitants. It can be the case, indeed, that following the diffusion of the platform, only a subset of population (i.e., those owning complementary assets, such as dwellings, spaces to host restaurants or entertainment activities; or those having at own disposition enough capital requirement to embark in new ventures) can benefit of the positive externalities (e.g., wider demand exposure) provided by Airbnb, thus increasing inequality among population and/or starting processes of displacement. Complementarily, local policy makers should be aware whether the effects highlighted on the entrepreneurial activity can pass through the whole local economy, inverting the highlighted declining economic conditions. In order to do so, this post-hoc analysis have conducted an additional model specification, where the dependent variables are not related to the entrepreneurial activity, but generally depict the economic conditions within a borgo (i.e., using all the methodological steps as reported in section 4.4.2)[80]. The following variables have been additionally tested: a) $GINI_{i,t}$ which represent the income inequality index within a Borgo *i* at time *t*; b) $POP_{i,t}$ representing the active population in a Borgo *i* at time *t*; c) $INCOME\text{-}EMP_{i,t}$ which represents the total income of employed people within the Borgo at a given time; d) $INCOME\text{-}EMPpc_{i,t}$ representing the per-capita value of the employed people income; e) $RENT\text{-}DW_{i,t}$ which represents the average long-term rental price for habitation-style dwellings in a given Borgo at time *t*; and f) $RENT\text{-}BUS_{i,t}$ that is the average long-term rental price for business-style facilities (shops, restaurants, etc.) in a Borgo *i* at time *t*. All variables, except $GINI_{i,t}$ (which varies between 0 and 1) have been log-transformed.

[Insert Table 4.11. here]

Results are available in Table 4.11. Multiple effects, in support of the whole local community, rather than to entrepreneurs only, are likely to hold. First, the Table shows that the entry and subsequent diffusion of Airbnb within the Borgo has no clear effects on income inequality, being all the leads coefficient not statistically significant. Furthermore, the analysis even finds that in the long run a weak negative effect of Airbnb entry on Gini coefficient exists, being it lower by 0.3 percentage points from T+4 onwards in treated Borghi. Second, closely tied with the global economic outlook of the Italian Borghi, which are under the risk of depopulation (as reported in section 4.3.), the econometric model shows that the entry of Airbnb has mitigating effects, being population active within the Borgo, 3% higher in the long run compared to untreated ones. Third, as long as it is shown (in previous paragraphs) that the entry of home-sharing can create novel entrepreneurial opportunities, complementarily the analyses find that also employed people can benefits of these externalities. In particular, income from employed activities is likely to significantly increase, concurring with an additional 2.9% in the long run. In monetary terms, this effect is likely to bring in the median borgo about 450k€ more per year in the long run from declared employed people's income. Complementarily, an average employee in a given Borgo is likely to benefits too, being the average per capita income higher by 1.6% (equivalently, in a median Borgo, higher by 280€

[80] Limitations to these analyses are discussed in section 4.7.1.

annually). Finally, any displacement processes are not found, being the long-term rentals for both habitation dwellings and business style spaces being not significantly different comparing treated and untreated Borghi.

4.7. Conclusions

This study has further produced additional findings to the flourishing debate on the side effects of home-sharing platforms on local economic welfare, or broadly, the externalities generated by the novel digital platforms to societal outcomes. This research enters this debate by providing a novel point of view since, while literature has often focused on empirical studies within cities (Barron et al., 2021; Chen et al., 2022; Burtch et al., 2018), it has provided an empirical application within a rural context taking advantage of a novel dataset on the Italian Borghi.

In doing this, this chapter analyzes whether the entry of Airbnb in a subset of Italian Borghi has generated significant effects on the local entrepreneurial activity, highlighting concurrent findings compared to the extant results. Indeed, as opposed to Burtch et al. (2018), results find that the roll out of Airbnb in these marginal areas has positive effects on entrepreneurial activity, being the number of active firms increasing, as well as the total income declared by entrepreneurs in a given borgo. Complementarily, the analyses have also shown the mechanisms behind these effects, pointing out that some sectors are the first one to benefits the entry of the platform (i.e., transport, restoration), still in the long run the positive externalities permute through all the value chain, positively impacting also primary (e.g., agriculture) and secondary (e.g., manufacturing) sectors. As opposed to the theoretical arguments of Burtch et al. (2018) (Acs & Armington, 2006; Block & Koellinger, 2009), it is possible to interpret these results in the light of the capability of the platform, which is able to provide a wider market exposure to the marginal areas, thus generating novel opportunities for prospective entrepreneurs (Foss & Klein, 2020). In other words, this chapter shows how Airbnb, in these contexts, plays the role of External Enabler a-là Davidsson (2015). Consistently to the estimates, this study also enlarges the knowledge upon home-sharing platform, showing that in specific contexts (i.e., rural areas or marginal destinations) the platform can serve as endogenous growth mechanism rather than an uncontrolled phenomenon feeding negative externalities such as residential displacement (Barron et al., 2021; Garcia-Lopez et al., 2020; Chen et al., 2022) or fierce competition with existing incumbents (Zervas et al., 2017).

4.7.1. Limitations and Future Developments

This research is not exempted from limitations, which can clearly pave the way for novel research streams within the academic and practitioner community. First, despite the study is one of the first tackling the diffusion of digital platforms in rural contexts, it has focused on a specific set of destinations, the Italian Borghi. Although, as reported in section 4.3., these destinations clearly depict areas experiencing marginal and declining economic conditions, still retaining potential valuable assets that are actually under-exploited, it can be worthy for future researchers to focus on different areas. In this sense, that future researchers should build upon the asymmetry between urban and rural areas, providing additional empirical evidence from other marginal destinations, assessing whether these effects are also cross-country different.

Second, despite data have information since 2009, which is actually at the beginning of Airbnb diffusion in Italy (i.e., the first Airbnb who opened in Italy was in June 2008), the dataset stops at the end of 2019, thus providing two main future directions as well as two limitations. On the one side, to the extent that the entry of Airbnb in our sample is largely focused between 2011 and 2014, the models only have, on average, five years to evaluate the long run effects of the home-sharing platform on the outcome variables. This is a limitation, in the sense that the analyses might not observe periods in which the diffusion of the platform has gone out of control, thus creating negative effects as those reported by the existing literature in cities (Barron et al., 2021; Garcia-Lopez et al., 2020; Chen et al., 2022; Carrasco-Farrè et al., 2022). However, an additional visual inspection of stage of diffusion of Airbnb (available in Appendix 6) has been conducted, showing that in treated Borghi the home-sharing platform is, in 2019, on average closed to the maturity stage of diffusion (i.e., the flatten part of the logistic curve). On the other side, the analysis stops right before the shock of Pandemic, which is likely to leave a remarkable footprint on the economic prospects of the Borghi in multiple ways. In this sense, future research can examine the combination of both factors (i.e., Airbnb diffusion and Pandemic outbreak), comparing the results with different market contexts and see whether home-sharing platforms can efficiently enhance post-Covid tourism recovery strategies or mitigate the devasting impact of Pandemic.

Finally, such analysis can be further exploited in two ways. First, in line with the recent phenomenon of Airbnb supply side professionalization (Dogru, 2020a; Chen et al., 2020b), this study does not consider whether differences in the effects of Airbnb exist if the local diffusion of the platform is driven by these professionals. It is plausible, indeed, that such "entrepreneurs" can significantly impact the entrepreneurial activity in local areas as long as they can bring larger capital investments (Dogru, 2020a) into the local community. Second, although our models efficiently control for various levels of control variables, it can be of interest of policy makers to understand whether specific resources at the local level (e.g., natural amenities or historical ones) may have boosted the effects of the treatment. To this end, future research may apply specific methods (e.g., causal forests) to shed a light upon the matching between platform and local resources.

References – Chapter 4

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Tables – Chapter 4

Table 4.1. Airbnb entries in Italian Borghi per year.

	Entry Year	# Borghi	% Borghi
Control Group	n.a.	71	26.30%
Treatment Group	2009	2	0.74%
	2010	19	7.04%
	2011	48	17.78%
	2012	55	20.37%
	2013	48	17.78%
	2014	21	7.78%
	2015	6	2.22%
	2016	0	0.00%
	2017	0	0.00%
	2018	0	0.00%
	2019	0	0.00%
	TOTAL	270	100.00%

Notes:

a) The two Borghi whose Airbnb entry date is 2009 will be excluded from the analysis because of absence of pre-treatment period.
b) Treatment assignment is when the first Airbnb in a given borgo has subscribed to the platform.
c) Control group is composed by those Borghi where no Airbnb have opened between 2009 and 2019.

Table 4.2. Descriptive Statistics.

VARIABLE	SOURCE	DESCRIPTION	MEAN	MEDIAN	STD. DEV	MIN	MAX
$Treat_i$	AirDNA	Dummy equals to 1 if Borgo i is treated (i.e., Airbnb entered), 0 otherwise	0,74	-	-	-	-
$Post_{i,t}$	AirDNA	Dummy equals to 1 if Borgo i is treated and the observation is recorded in the post-treatment phase	0,53	-	-	-	-
$AirbnbPenetration_{i,t}$	AirDNA	Number of active Airbnb in a Borgo i at time t, per squared kilometer.	3,09	0,02	39,71	0,00	1144,28
$INCOME_{i,t}$	MEF	Income from "entrepreneurial activity" declared in a Borgo i at year t	2.366.134,97 €	1.529.716,00 €	2.451.192,87 €	- €	14.854.862,00 €
$INCOMEpc_{i,t}$	MEF	Per capita income from "entrepreneurial activity" declared in a Borgo i at year t	16.632,68 €	16.149,56 €	4.933,44 €	- €	37.671,13 €
$FIRMS_{i,t}$	CHC	Number of active firms in a Borgo i at year t	400,88	264,00	375,50	0,00	1836,00
$PR_{i,t}$	CHC	Number of active firms in the primary sector (e.g., agriculture, fishing) in a Borgo i at year t	115,19	71,00	126,16	0,00	1155,00
$MFCG_{i,t}$	CHC	Number of active firms in the secondary sector (manufacturing) in a Borgo i at year t	37,46	21,00	41,80	0,00	285,00
$TRD_{i,t}$	CHC	Number of active firms in the trade sector in a Borgo i at year t	87,43	55,00	95,48	0,00	537,00
$TRSP_{i,t}$	CHC	Number of active firms in the transportation sector in a Borgo i at year t	9,64	5,00	11,50	0,00	67,00
$HSP_{i,t}$	CHC	Number of active firms in the hospitality in a Borgo i at year t	32,61	21,00	34,35	0,00	269,00
$FIN_{i,t}$	CHC	Number of active firms in the financial services sector in a Borgo i at year t	5,56	3,00	6,91	0,00	54,00
$RE_{i,t}$	CHC	Number of active firms in the real estate sector in a Borgo i at year t	9,86	4,00	15,21	0,00	95,00
$TA\text{-}NOL_{i,t}$	CHC	Number of active firms in the travel-agency and support services sector in a Borgo i at year t	7,77	4,00	9,84	0,00	75,00
$ENT_{i,t}$	CHC	Number of active firms in the entertainment in a Borgo i at year t	4,21	2,00	5,97	0,00	49,00
$HotelBeds_{i,t}$	ISTAT	Number of hotel beds in a Borgo i at year t	262,75	72,00	631,61	0,00	6608,00
$GDP_{i,n,t}$	ISTAT	Provincial (NUTS3 n to which the Borgo i belongs) yearly GDP [in millions]	89.255,23 €	48.309,50 €	84.402,87 €	4.528,20 €	399.339,80 €
$UnemplRate_{i,n,t}$	ISTAT	Provincial (NUTS3 n to which the Borgo i belongs) yearly Unemployment Rate (x100)	11,06	9,90	4,97	3,18	23,42

Notes:

a) MEF = Italian Ministry for Economy and Finance (https://www.mef.gov.it)
b) CHC = Italian Chamber of Commerce (https://www.to.camcom.it)
c) Statistics refer to the whole sample of 270 Borghi, observed between 2009 and 2019.

Table 4.3. Effects of Airbnb entry on local entrepreneurial activity.

	$INCOME_{i,t}$	$INCOMEpc_{i,t}$	$FIRMS_{i,t}$
T-2 backwards	-0.048	0.003	-0.010
	(0.044)	(0.013)	(0.023)
	(0.276)	(0.795)	(0.650)
T0	0.038	0.019	0.000
	(0.047)	(0.013)	(0.025)
	(0.412)	(0.146)	(0.989)
T+1	0.068	0.024+	0.001
	(0.049)	(0.014)	(0.026)
	(0.168)	(0.095)	(0.982)
T+2	0.100+	0.027+	0.024
	(0.052)	(0.015)	(0.028)
	(0.054)	(0.066)	(0.388)
T+3	0.135*	0.024	0.050+
	(0.054)	(0.016)	(0.029)
	(0.013)	(0.125)	(0.081)
T+4 onwards	0.236***	0.053***	0.050+
	(0.052)	(0.015)	(0.028)
	(0.000)	(0.000)	(0.071)
Constant	13.626**	9.972***	55.342***
	(4.436)	(1.269)	(2.338)
	(0.002)	(0.000)	(0.000)
Control Variables $X_{i,t}$	Yes	Yes	Yes
IndividualFE η and TimeFE τ	Yes	Yes	Yes
N	2,872	2,866	2,853
Overall R2	0.140	0.005	0.000
Between R2	0.181	0.074	0.000
Within R2	0.122	0.255	0.223

Notes:

a) *** p<0.001; ** p<0.01; * p<0.05; + p<0.10. Bootstrapped standard errors and p-value in parentheses.
b) Dependent variables are log-transformed.
c) Leads and Lags must be interpreted compared to T-1 (one year before the treatment assignment).

Table 4.4. Standard DID approach: effects on local entrepreneurial activity.

	$INCOME_{i,t}$	$INCOMEpc_{i,t}$	$FIRMS_{i,t}$
$DID_{i,t}$	0.104+	0.023	0.017
	(0.061)	(0.015)	(0.011)
	(0.086)	(0.127)	(0.108)
Constant	69.801*	10.836	11.286*
	(34.703)	(34.578)	(5.684)
	(0.045)	(0.754)	(0.048)
Control Variables $X_{i,t}$	Yes	Yes	Yes
IndividualFE η and TimeFE τ	Yes	Yes	Yes
N	2,872	2,866	2,853
Overall R2	0.001	0.009	0.000
Between R2	0.001	0.059	0.001
Within R2	0.114	0.252	0.221

Notes

a) *** p<0.001; ** p<0.01; * p<0.05; + p<0.10. Bootstrapped standard errors and p-value in parentheses.
b) Dependent variables are log-transformed.
c) $DID_{i,t}$ = 1 if the borgo *i* is treated and t >= treatment timing of borgo *i*.

Table 4.5. Continuous treatment approach: effects on local entrepreneurial activity.

	$INCOME_{i,t}$	$INCOMEpc_{i,t}$	$FIRMS_{i,t}$
ATE $lnAirbnbPenetration_{i,t}$	0.141+	0.043***	0.025**
	(0.080)	(0.011)	(0.008)
	(0.080)	(0.000)	(0.004)
Control Variables $X_{i,t}$	Yes	Yes	Yes
IndividualFE η and TimeFE τ	Yes	Yes	Yes
N	2,872	2,872	2,872

Notes

a) *** p<0.001; ** p<0.01; * p<0.05; + p<0.10. Bootstrapped standard errors and p-value in parentheses.
b) Dependent variables are log-transformed.
c) ATE = Average Treatment Effect for continuous treatment (Airbnb Penetration, log transformed).

Table 4.6. Effects of Airbnb entry by market sector.

	PR	MFCG	TRD	TRSP	HSP	FIN	RE	TA-NOL	ENT
$lnFIRMS_{i,t-1}$	0.189***	0.137***	0.169***	0.090***	0.148***	0.069***	0.069***	0.110***	0.087***
	(0.013)	(0.013)	(0.012)	(0.014)	(0.011)	(0.017)	(0.015)	(0.017)	(0.017)
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
T-2 back	0.020	-0.017	0.032+	-0.023	-0.004	0.027	-0.001	-0.016	-0.010
	(0.019)	(0.020)	(0.018)	(0.021)	(0.016)	(0.025)	(0.022)	(0.026)	(0.026)
	(0.297)	(0.394)	(0.076)	(0.284)	(0.803)	(0.267)	(0.967)	(0.548)	(0.685)
T0	0.016	0.016	-0.005	0.009	0.015	-0.002	0.049*	0.058*	0.001
	(0.019)	(0.020)	(0.018)	(0.021)	(0.016)	(0.025)	(0.022)	(0.026)	(0.026)
	(0.391)	(0.411)	(0.800)	(0.678)	(0.349)	(0.950)	(0.023)	(0.024)	(0.976)
T+1	0.014	0.016	-0.016	0.040+	0.031+	0.005	0.055*	0.045	0.050+
	(0.020)	(0.021)	(0.019)	(0.022)	(0.017)	(0.026)	(0.023)	(0.027)	(0.027)
	(0.474)	(0.430)	(0.396)	(0.073)	(0.072)	(0.842)	(0.016)	(0.104)	(0.067)
T+2	0.041+	0.032	-0.008	0.067**	0.053**	0.013	0.063**	0.042	0.084**
	(0.021)	(0.022)	(0.020)	(0.024)	(0.018)	(0.028)	(0.024)	(0.029)	(0.029)
	(0.059)	(0.151)	(0.683)	(0.005)	(0.003)	(0.645)	(0.010)	(0.149)	(0.004)
T+3	0.050*	0.065**	-0.000	0.097***	0.066***	0.007	0.111***	0.046	0.122***
	(0.022)	(0.023)	(0.021)	(0.025)	(0.019)	(0.029)	(0.025)	(0.031)	(0.030)
	(0.026)	(0.005)	(0.992)	(0.000)	(0.001)	(0.804)	(0.000)	(0.131)	(0.000)
T+4 on	0.043*	0.077***	-0.014	0.108***	0.086***	0.014	0.108***	0.079**	0.115***
	(0.022)	(0.023)	(0.021)	(0.024)	(0.018)	(0.028)	(0.025)	(0.030)	(0.029)
	(0.049)	(0.001)	(0.489)	(0.000)	(0.000)	(0.625)	(0.000)	(0.008)	(0.000)
Constant	3.060***	2.344***	2.884***	1.240***	2.072***	0.800***	1.223***	0.704***	0.633***
	(0.114)	(0.118)	(0.109)	(0.127)	(0.096)	(0.147)	(0.130)	(0.156)	(0.154)
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$X_{i,t}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
η and τ	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,652	2,652	2,652	2,652	2,652	2,652	2,652	2,652	2,652
Overall R2	0.526	0.606	0.763	0.274	0.659	0.332	0.274	0.417	0.340
Between R2	0.581	0.689	0.839	0.307	0.715	0.411	0.314	0.478	0.400
Within R2	0.208	0.192	0.169	0.163	0.207	0.122	0.114	0.260	0.122

Notes:

a) *** p<0.001; ** p<0.01; * p<0.05; + p<0.10. Bootstrapped standard errors and p-value in parentheses.
b) Dependent variables are log-transformed.
c) PR = Primary Sector (e.g., agriculture or fishing); MFCG = Secondary Sector (Manufacturing); TRD = Trade; TRSP = Transportation; HSP = Hospitality (e.g., restaurants & traditional hospitality); FIN = Financial Services; RE = Real Estate; TA-NOL = Travel Agencies & Support services; ENT = Entertainment.
d) Leads and Lags must be interpreted compared to T-1 (one year before the treatment assignment).
e) T-2 back = from 2 years before treatment to the first available lag; T+4 on = from 4 years after treatment to the last available obs.

Table 4.7. Placebo-Falsification #1 test.

	$Y_{i,t} = INCOME_{i,t}$			$Y_{i,t} = INCOMEpc_{i,t}$			$Y_{i,t} = FIRMS_{i,t}$		
	T0	T+1o	DID	T0	T+1o	DID	T0	T+1o	DID
Mean	0.601	0.577	0.458	0.617	0.631	0.569	0.339	0.464	0.613
Std. Dev.	0.252	0.234	0.202	0.243	0.230	0.262	0.308	0.287	0.255
Min	0.055	0.075	0.050	0.043	0.070	0.017	0.000	0.003	0.006
Median	0.633	0.561	0.426	0.639	0.651	0.581	0.242	0.465	0.644
Max	0.999	0.999	0.994	0.997	0.998	0.999	0.999	0.999	0.999

Notes:

a) T+1o = from one year after treatment onwards.
b) The main descriptive statistics of the p-values of the coefficients T0 (treatment assignment), T+1 (from one year after the treatment) and DID is displayed.
c) Both T0 and T+1 onwards are from a panel event study approach.
d) DID is from a standard difference in difference approach.
e) The distribution is based on 1,000 random treatment allocations of the treatment to treated units in the pre-treatment phase.

Table 4.8. Placebo-Falsification #2 test.

	$Y_{i,t} = INCOME_{i,t}$						$Y_{i,t} = INCOMEpc_{i,t}$						$Y_{i,t} = FIRMS_{i,t}$					
	T0	T+1	T+2	T+3	T+4o	DID	T0	T+1	T+2	T+3	T+4o	DID	T0	T+1	T+2	T+3	T+4o	DID
Mean	0.733	0.626	0.505	0.433	0.318	0.416	0.586	0.540	0.491	0.446	0.362	0.499	0.634	0.562	0.481	0.435	0.297	0.504
Std. Dev.	0.244	0.291	0.316	0.336	0.336	0.230	0.262	0.279	0.280	0.300	0.309	0.286	0.255	0.268	0.291	0.307	0.309	0.292
Min	0.015	0.001	0.000	0.000	0.000	0.001	0.002	0.009	0.004	0.000	0.000	0.008	0.014	0.005	0.000	0.000	0.000	0.001
Median	0.813	0.711	0.543	0.376	0.162	0.357	0.606	0.547	0.477	0.418	0.295	0.495	0.670	0.585	0.469	0.422	0.174	0.514
Max	0.999	0.999	0.998	0.999	0.999	0.996	0.999	0.999	0.999	0.999	0.998	0.999	0.999	0.998	0.999	0.998	0.998	0.999

Notes:

a) T+4o = from four year after treatment onwards.
b) The main descriptive statistics of the p-values of the coefficients T0 (treatment assignment), T+1 (one year after the treatment), T+2 (two years after the treatment), T+3 (three years after the treatment), T+1o (from four years after the treatment onwards) and DID is displayed.
c) Both T0, T+1, T+2, T+3 and T+4 onwards are from a panel event study approach.
d) DID is from a standard difference in difference approach.
e) The distribution is based on 1,000 random treatment allocations of the treatment to units owning to the control group.

Table 4.9a. 2SLS Approach with Exposure-Design IV (Alternative A – use predicted values of treatment allocation)

	$INCOME_{i,t}$	$INCOMEpc_{i,t}$	$FIRMS_{i,t}$
T-2 backwards	-0.036	0.010	-0.005
	(0.052)	(0.015)	(0.027)
	(0.490)	(0.502)	(0.855)
T0	0.077	0.017	0.042
	(0.058)	(0.017)	(0.031)
	(0.182)	(0.296)	(0.168)
T+1	0.109+	0.020	0.051
	(0.064)	(0.018)	(0.034)
	(0.089)	(0.263)	(0.133)
T+2	0.123+	0.011	0.052
	(0.066)	(0.019)	(0.035)
	(0.063)	(0.560)	(0.134)
T+3	0.133+	0.029	0.059+
	(0.068)	(0.019)	(0.036)
	(0.050)	(0.139)	(0.099)
T+4 onwards	0.104	0.035+	0.079*
	(0.070)	(0.020)	(0.037)
	(0.136)	(0.081)	(0.031)
Constant	12.543**	9.881***	53.246***
	(4.408)	(1.273)	(2.314)
	(0.004)	(0.000)	(0.000)
Control Variables $X_{i,t}$	Yes	Yes	Yes
IndividualFE η and TimeFE τ	Yes	Yes	Yes
N	2,872	2,866	2,853
Overall R2	0.105	0.002	0.000
Between R2	0.120	0.057	0.000
Within R2	0.115	0.251	0.223

Notes:

a) *** p<0.001; ** p<0.01; * p<0.05; + p<0.10. Bootstrapped standard errors and p-value in parentheses.
b) Dependent variables are log-transformed.
c) Leads and Lags must be interpreted compared to T-1 (one year before the treatment assignment).
d) Treatment allocation is based on the first stage, employing an exposure design approach, with IV = $\ln(ResidentialDwellings_i)*AirbnbSearchQuery_t$.
e) Estimated Treatment Allocation if $Pr[DID_{i,t}] >= 0.75$.

Table 4.9b. 2SLS Approach with Exposure-Design IV (Alternative B – control function approach)

	$INCOME_{i,t}$ [a]	$INCOME_{i,t}$ [b]	$INCOMEpc_{i,t}$ [a]	$INCOMEpc_{i,t}$ [b]	$FIRMS_{i,t}$ [a]	$FIRMS_{i,t}$ [b]
T-2 backwards	-0.045	-0.032	0.007	0.009	0.020	0.020
	(0.052)	(0.052)	(0.015)	(0.015)	(0.020)	(0.020)
	(0.387)	(0.542)	(0.638)	(0.542)	(0.328)	(0.324)
T0	-0.022	0.009	0.039	0.043	-0.040	-0.039
	(0.098)	(0.098)	(0.027)	(0.028)	(0.038)	(0.038)
	(0.824)	(0.929)	(0.159)	(0.116)	(0.293)	(0.303)
T+1	0.010	0.062	0.043	0.051+	-0.039	-0.038
	(0.096)	(0.098)	(0.027)	(0.027)	(0.037)	(0.038)
	(0.916)	(0.528)	(0.112)	(0.063)	(0.301)	(0.321)
T+2	0.043	0.108	0.047+	0.057*	-0.012	-0.011
	(0.097)	(0.099)	(0.027)	(0.028)	(0.038)	(0.039)
	(0.655)	(0.276)	(0.082)	(0.040)	(0.755)	(0.783)
T+3	0.078	0.150	0.044	0.055+	-0.006	-0.004
	(0.097)	(0.101)	(0.027)	(0.028)	(0.038)	(0.039)
	(0.420)	(0.135)	(0.109)	(0.051)	(0.882)	(0.910)
T+4 onwards	0.182+	0.264**	0.075**	0.088**	0.012	0.013
	(0.095)	(0.100)	(0.027)	(0.028)	(0.037)	(0.039)
	(0.057)	(0.008)	(0.005)	(0.002)	(0.752)	(0.737)
Constant	14.550***	14.598***	9.520***	9.514***	5.429***	5.420***
	(0.363)	(0.362)	(0.101)	(0.099)	(0.137)	(0.144)
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Linear CF	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic CF	No	Yes	No	Yes	No	Yes
Control Variables $X_{i,t}$	Yes	Yes	Yes	Yes	Yes	Yes
IndividualFE η and TimeFE τ	Yes	Yes	Yes	Yes	Yes	Yes
N	2,535	2,535	2,529	2,529	2,525	2,525
Overall R2	0.114	0.067	0.002	0.061	0.010	0.008
Between R2	0.112	0.059	0.035	0.028	0.009	0.007
Within R2	0.123	0.126	0.256	0.257	0.065	0.065

Notes:

a) *** p<0.001; ** p<0.01; * p<0.05; + p<0.10. Bootstrapped standard errors and p-value in parentheses.
b) Dependent variables are log-transformed.
c) Leads and Lags must be interpreted compared to T-1 (one year before the treatment assignment).
d) Models denoted with [a] employ a linear control function, while models denoted with [b] employ a quadratic control function.
e) Linear CF = linear form of the residuals in the first stage are included.
f) Quadratic CF = quadratic form of the residuals in the first stage are included.

Table 4.10. CEM Approach.

	$INCOME_{i,t}$	$INCOMEpc_{i,t}$	$FIRMS_{i,t}$
T-2 backwards	-0.035	0.004	-0.005
	(0.037)	(0.013)	(0.011)
	(0.338)	(0.737)	(0.682)
T0	0.024	0.018	0.007
	(0.040)	(0.014)	(0.012)
	(0.545)	(0.189)	(0.584)
T+1	0.043	0.020	0.013
	(0.042)	(0.015)	(0.013)
	(0.307)	(0.171)	(0.315)
T+2	0.054	0.025	0.013
	(0.044)	(0.016)	(0.014)
	(0.221)	(0.108)	(0.333)
T+3	0.062	0.021	0.037**
	(0.046)	(0.016)	(0.014)
	(0.184)	(0.200)	(0.008)
T+4 onwards	0.114*	0.046**	0.029*
	(0.045)	(0.016)	(0.014)
	(0.011)	(0.004)	(0.034)
Constant	14.076***	9.512***	5.449***
	(0.191)	(0.065)	(0.061)
	(0.000)	(0.000)	(0.000)
Control Variables $X_{i,t}$	Yes	Yes	Yes
IndividualFE η and TimeFE τ	Yes	Yes	Yes
N	2,595	2,589	2,580
Overall R2	0.048	0.017	0.039
Between R2	0.044	0.000	0.063
Within R2	0.128	0.274	0.174

Notes:

a) *** p<0.001; ** p<0.01; * p<0.05; + p<0.10. Bootstrapped standard errors and p-value in parentheses.
b) Dependent variables are log-transformed.
c) Leads and Lags must be interpreted compared to T-1 (one year before the treatment assignment).
d) Sample is based on CEM (see Section 5.3.3.)

Table 4.11. Policy makers implications.

	$GINI_{i,t}$	$POP_{i,t}$	$INCOME\text{-}EMP_{i,t}$	$INCOME\text{-}EMPpc_{i,t}$	$RENT\text{-}DW_{i,t}$	$RENT\text{-}BUS_{i,t}$
T-2 backwards	-0.001	-0.001	-0.006	-0.001	0.003	-0.005
	(0.001)	(0.003)	(0.005)	(0.004)	(0.010)	(0.010)
	(0.339)	(0.621)	(0.218)	(0.778)	(0.733)	(0.624)
T0	-0.000	0.003	0.009	0.005	-0.005	0.000
	(0.001)	(0.003)	(0.005)	(0.004)	(0.011)	(0.010)
	(0.883)	(0.324)	(0.116)	(0.269)	(0.671)	(0.971)
T+1	-0.001	0.007*	0.013*	0.009*	0.004	0.004
	(0.001)	(0.003)	(0.006)	(0.005)	(0.011)	(0.011)
	(0.590)	(0.018)	(0.022)	(0.045)	(0.704)	(0.747)
T+2	-0.001	0.011***	0.020**	0.013*	-0.001	-0.006
	(0.001)	(0.003)	(0.006)	(0.005)	(0.012)	(0.012)
	(0.298)	(0.000)	(0.001)	(0.011)	(0.956)	(0.624)
T+3	-0.001	0.017***	0.022***	0.014**	-0.007	-0.019
	(0.001)	(0.003)	(0.006)	(0.005)	(0.012)	(0.012)
	(0.504)	(0.000)	(0.001)	(0.005)	(0.592)	(0.118)
T+4 onwards	-0.003+	0.030***	0.029***	0.016**	-0.011	-0.012
	(0.001)	(0.003)	(0.006)	(0.005)	(0.012)	(0.012)
	(0.058)	(0.000)	(0.000)	(0.001)	(0.362)	(0.293)
Constant	0.292**	7.740***	17.414***	10.430***	-0.202	-0.347
	(0.113)	(0.016)	(0.523)	(0.419)	(0.984)	(0.963)
	(0.009)	(0.000)	(0.000)	(0.000)	(0.837)	(0.718)
Control Variables $X_{i,t}$	Yes	Yes	Yes	Yes	Yes	Yes
η and τ	Yes	Yes	Yes	Yes	Yes	Yes
N	2,872	2,866	2,872	2,872	2,810	2,746
Overall R2	0.039	0.061	0.017	0.052	0.106	0.102
Between R2	0.023	0.082	0.018	0.039	0.085	0.092
Within R2	0.195	0.343	0.415	0.351	0.341	0.291

Notes:

a) *** p<0.001; ** p<0.01; * p<0.05; + p<0.10. Bootstrapped standard errors and p-value in parentheses.

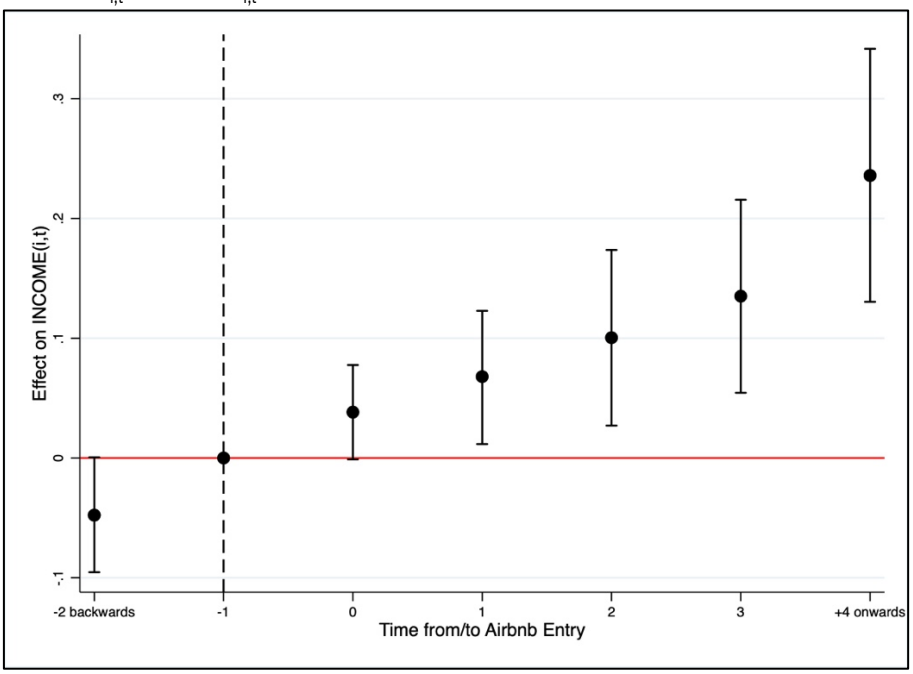
b) Dependent variables are log-transformed (except for GINI).

c) Leads and Lags must be interpreted compared to T-1 (one year before the treatment assignment).

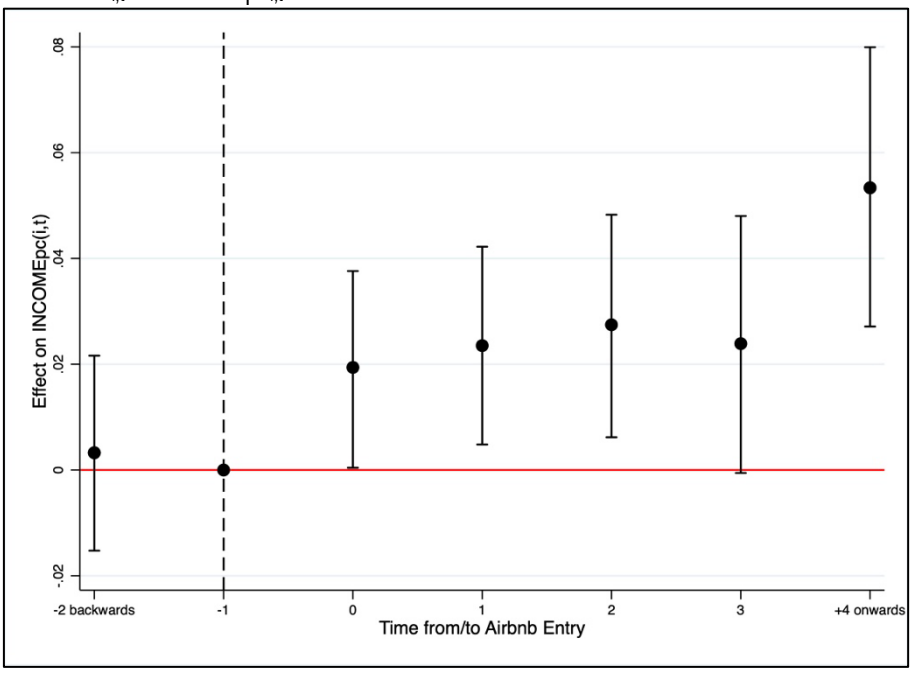
Figures – Chapter 4

Figure 4.1. Effects of Airbnb on local entrepreneurial activity: event study plot.

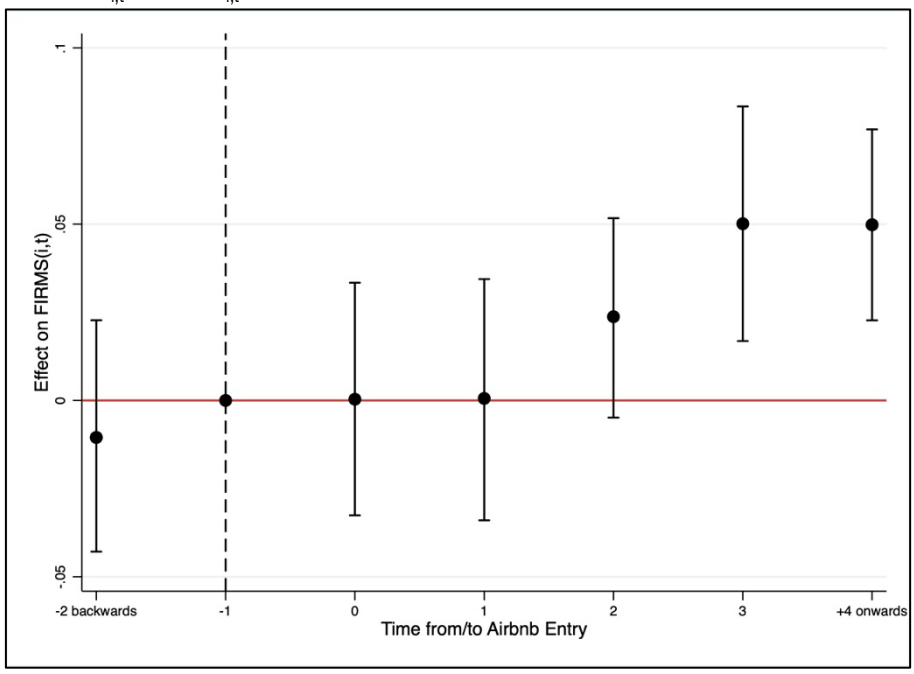
Panel A. $Y_{i,t} = INCOME_{i,t}$



Panel B. $Y_{i,t} = INCOMEpc_{i,t}$



Panel C. $Y_{i,t} = FIRMS_{i,t}$

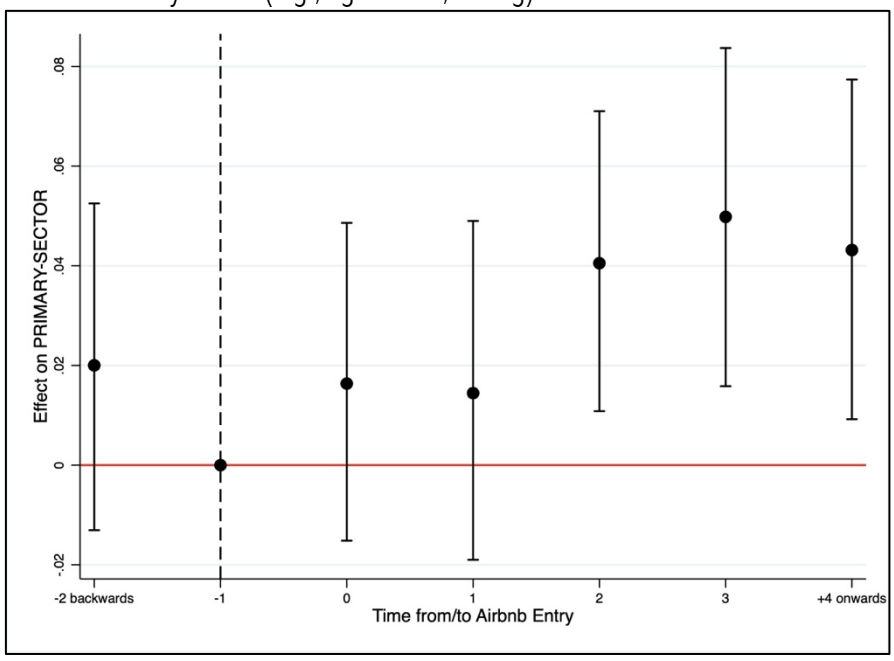


Notes:

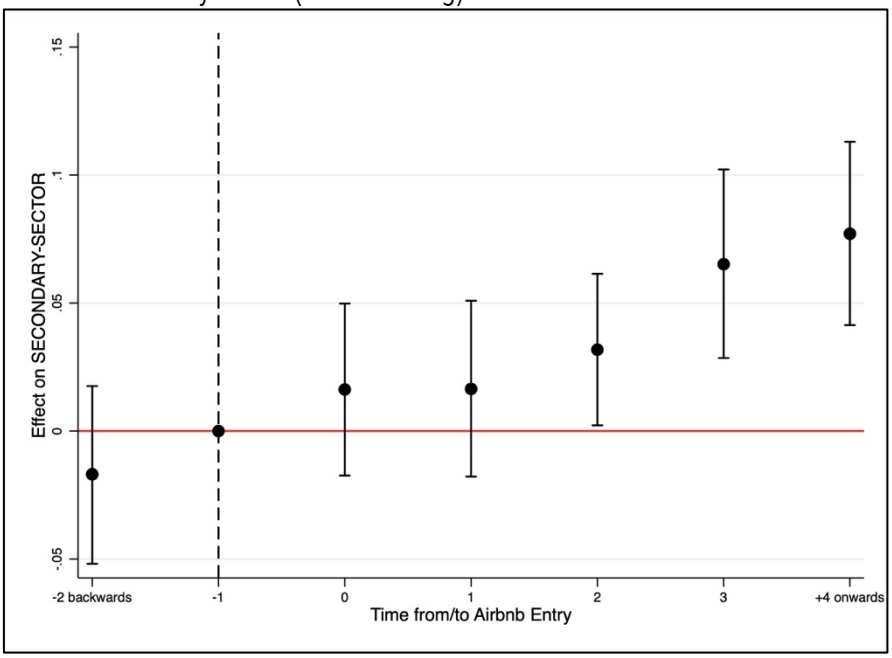
a) Panel A = dependent variable is the total income from entrepreneurial activity declared in a given borgo in a given year ($INCOME_{i,t}$). Panel B = dependent variable is the per-capita income from entrepreneurial activity declared in a given borgo in a given year ($INCOMEpc_{i,t}$). Panel C = dependent variable is the number of firms (of all typology) in a given borgo in a given year ($FIRMS_{i,t}$).
b) 90% confidence intervals based on bootstrapped standard errors are displayed.
c) "-2 backwards" represents the treatment effect from 2 years before the treatment assignment to the first data available within our dataset.
d) "+4 onwards" represents the treatment effect starting from 2 years after the treatment assignment to the latest data available within our dataset.
e) T-1 (one year before the treatment assignment) is the reference baseline.

Figure 4.2. Effects of Airbnb by industrial sector: event study plot.

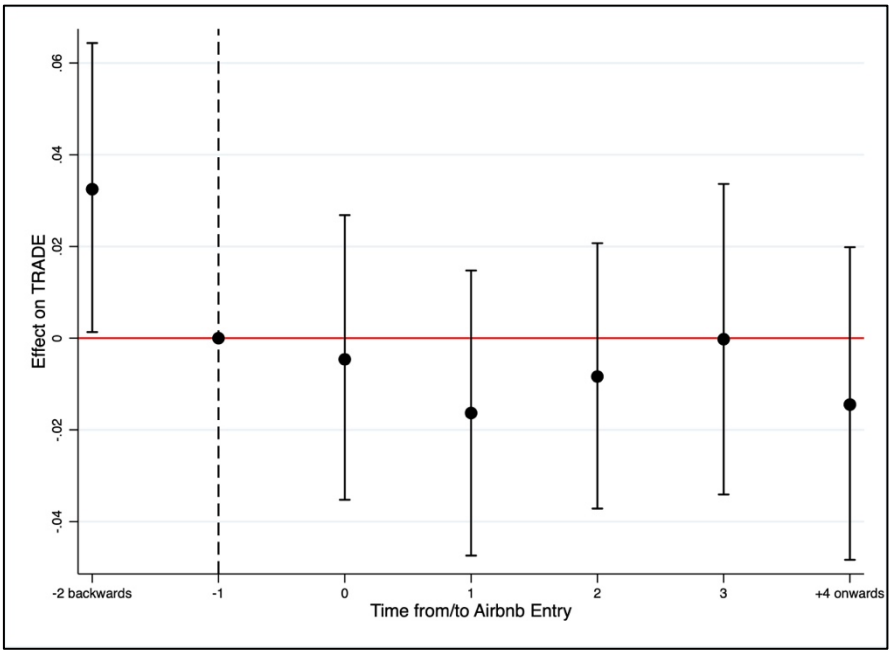
Panel A. Primary Sector (e.g., agriculture, fishing)



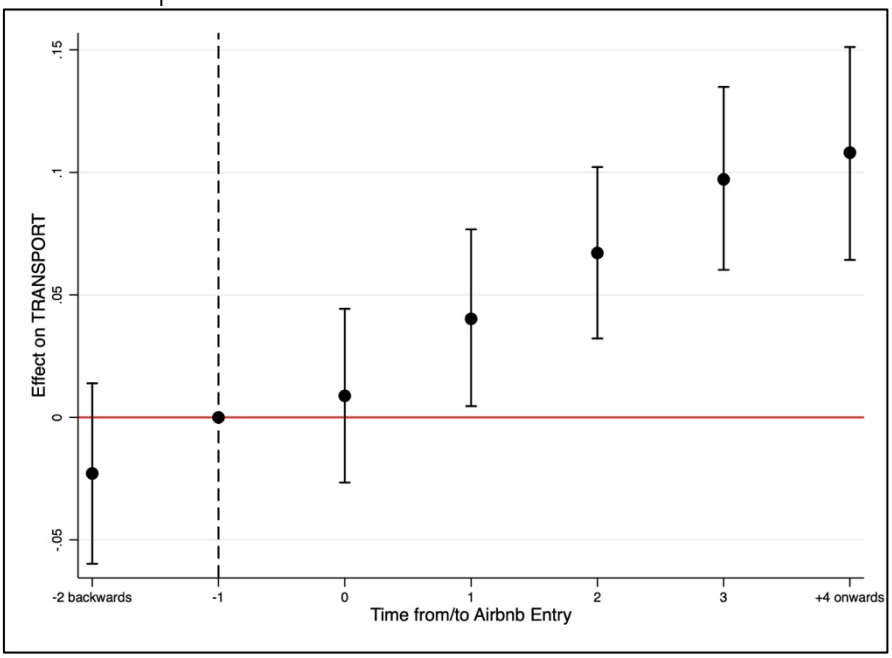
Panel B. Secondary Sector (manufacturing)



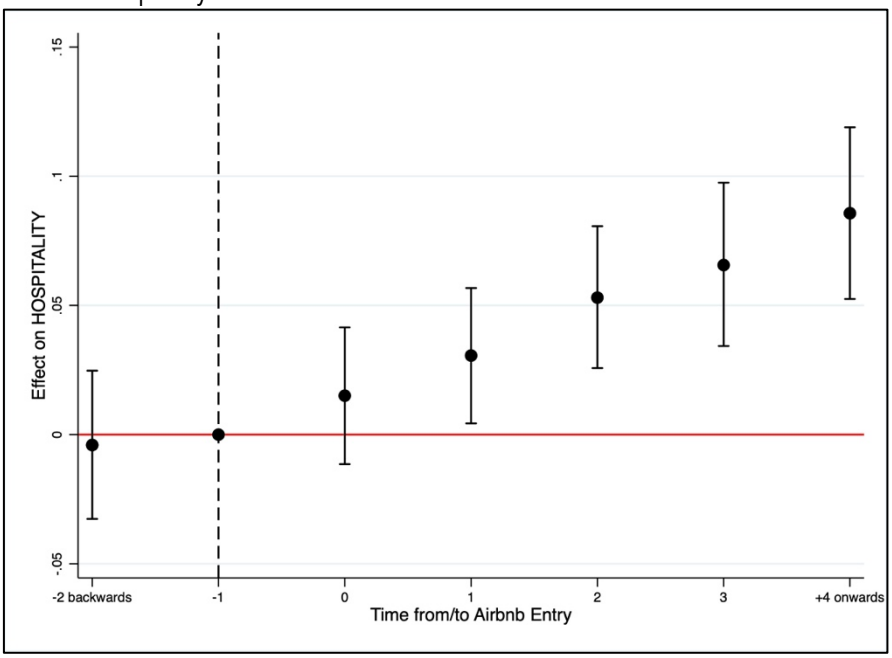
Panel C. Trade.



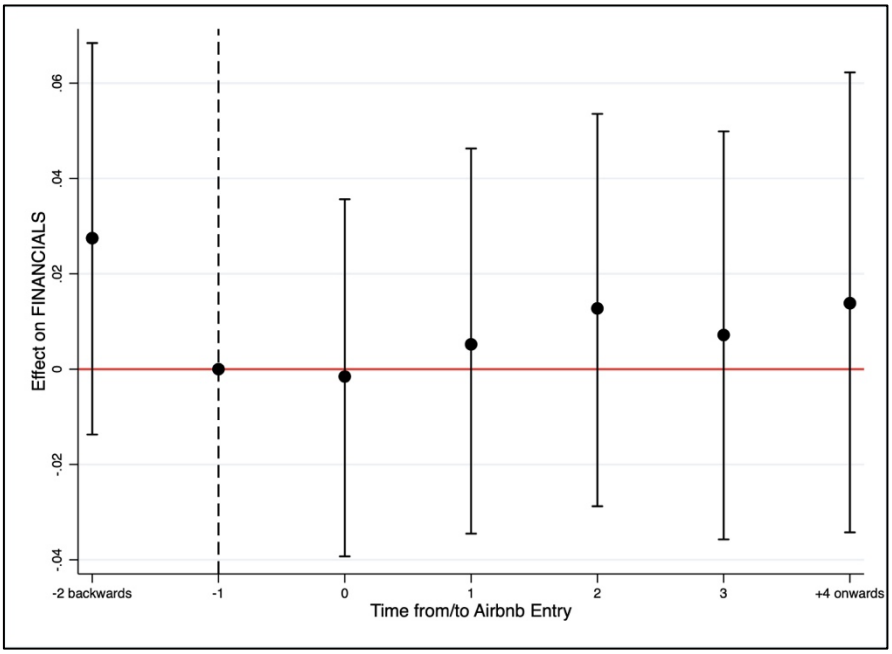
Panel D. Transportation.



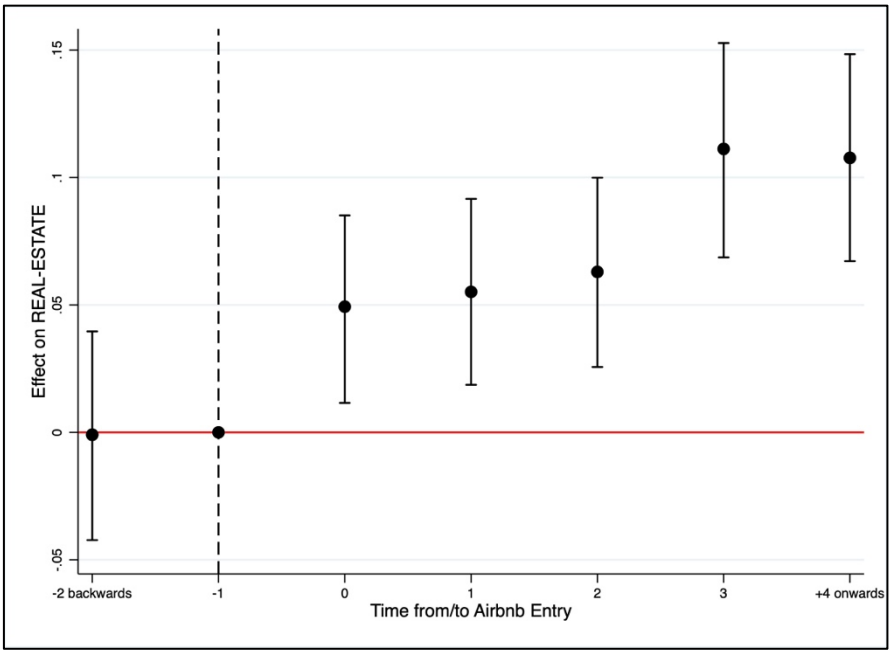
Panel E. Hospitality.



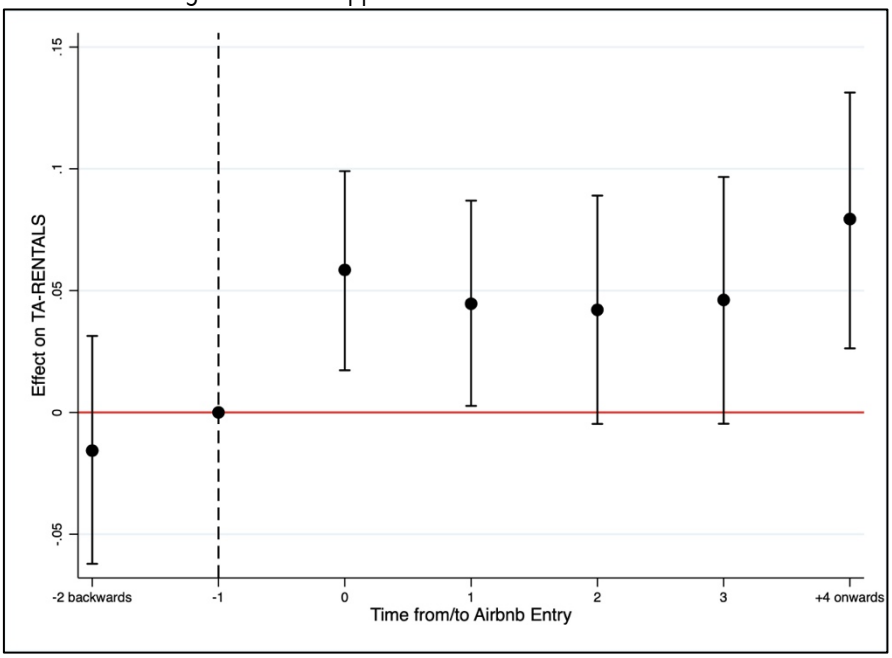
Panel F. Financial Services.



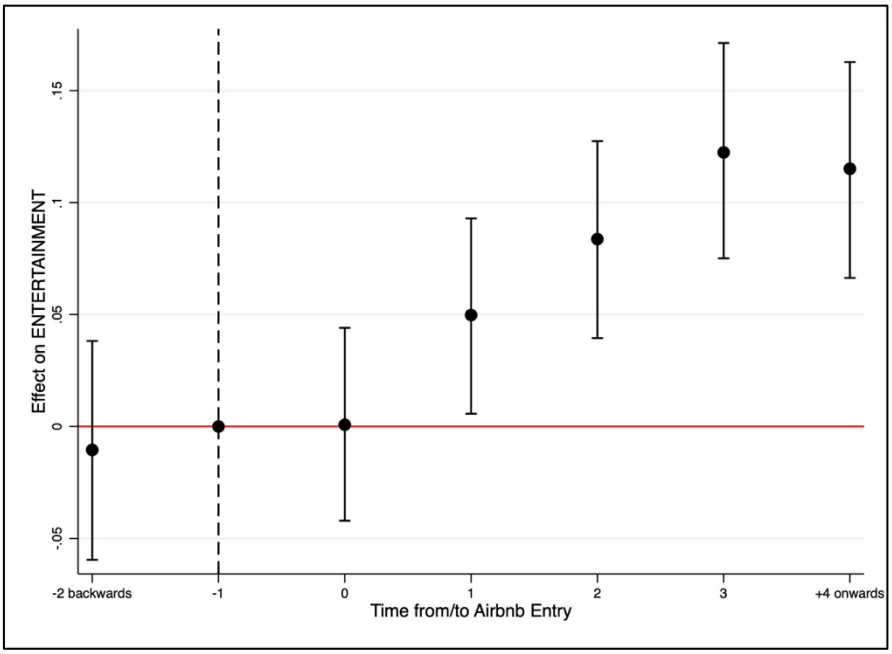
Panel G. Real Estate Services.



Panel H. Travel Agencies and Support Services.



Panel I. Entertainment Services.



Notes:

a) 90% confidence intervals based on bootstrapped standard errors are displayed.
b) "-2 backwards" represents the treatment effect from 2 years before the treatment assignment to the first data available within our dataset.
c) "+4 onwards" represents the treatment effect starting from 2 years after the treatment assignment to the latest data available within our dataset.
d) T-1 (one year before the treatment assignment) is the reference baseline.
e) Plots are based on the estimates displayed in Table 6.

Conclusion

This doctoral dissertation provides an in-depth investigation of the world-known Airbnb platform, adopting multiple perspective to empirically analyze its growth, the strategies adopted by its producers and the effects of its diffusion on local economic outcomes.

The main contribution of this dissertation, as well as its *fil rouge* throughout the entire work, is the proposition of a novel framework upon which intending and studying digital platforms. Indeed, as opposed to the common literature which has always though and studied platforms as global *fictitious* markets (Kim et al., 2022), namely "without borders" (Stallkamp & Schotter, 2021), this dissertation argues that multiple platforms (e.g., Airbnb, Uber) own a set of specific characteristics which make the economics of this two-sided market different from others. What is special about Airbnb, indeed, is that while supply and demand are met in a digital marketplace (just like global platforms as Amazon), the services offered on platform (as in Uber) are *spatially* localized, thus responding to specific logics of spatial concentration and competition.

In this vein, this work has firstly tackled one of the key concepts in Industrial Organization field, studying the magnitude of cross-side network externalities (Katz & Shapiro, 1985; Evans, 2003) on Airbnb platform, showing the heterogeneous indirect effects are likely to exists as their intensity is shaped by the local industry structure (either on the supply competition side or the demand one). Second, this dissertation, arguing that strategic decisions of Airbnb service providers are shaped by *local* industry variables, revises the determinants of two strategic decisions, entry and pricing, also analyzing the differences between small-scale (non-professional) hosts and large-scale (professional) ones (Dogru et al., 2020). On the one hand, taking a *meso* level perspective (Fischer & Nijkamp, 2009; Sternberg, 2009; Davidsson & Wiklund, 2001) and adopting the External Enabler framework (Davidsson, 2015), the second chapter has shown that local market conditions shape in different ways the entry dynamics of Airbnb hosts into the platform, with large-scale (professional) hosts responding to more sophisticated locally bounded effects (e.g., information, clustering, and peer competition and carrying capacity Carree & Thurik, 1999). On the other hand, employing a causal inference approach with continuous treatment (Callaway et al., 2021), the third chapter has shown how Airbnb hosts vary prices in response to demand shock. Consistently with the previous findings on the entry process, this chapter confirms what while non-professional hosts pricing decisions is mainly driven by hedonic-style variables or local spatial autocorrelation of the phenomenon, professional service providers vary prices upward in response to positive demand shocks. Finally, adopting the opposite perspective, the last chapter of the dissertation studies whether the local diffusion of the platform has effects on local entrepreneurial activity in marginal economic areas, complementing the debated literature on the effects of platforms on entrepreneurial activity (Burtch et al., 2018; von Briel et al., 2018) or, specifically, the effects of Airbnb on local welfare (Garcia-Lopez et al., 2020; Barron et al., 2021; Chen et al., 2022; Farronato & Fradkin, 2022; Zervas et al.,

2017). To this end, the fourth study shows that in such declining economic conditions Airbnb efficiently acts as enabler of entrepreneurial acts (Davidsson et al., 2015), with value creation effects happening at different point in time (i.e., increasing over time) and differently across different sectors (i.e., from sectors closer to tourism to more distant ones). In this sense, positive spillover effects for local residents are denoted.

Although generally referring to digital platforms, this work provides a precise overview on the long-debated phenomenon of Airbnb, which has become, today, one of the leading players, if not the leader, of the touristic industry. In line with different theoretical argumentations, proven by multiple econometric analyses, the dissertation has shown that Airbnb unveils a very complex mechanisms shaped by heterogeneous network effects, a clearly segmented producer side, where professionals and non-professional entrepreneurs co-exist and interact one each other, and not-obvious spillover effects deriving from its local diffusion. In this sense, on the one side this thesis has shown the challenges faced by practitioners when managing a complex platform such Airbnb, where, for instance, the same shock can result in different outcomes across different marketplaces (see chapter 1), or where easing transitions from small to large scale entrepreneurial effort can provide higher profitability to the platform (see chapter 2 and 3). On the other side, with peculiar reference to policy purposes, this dissertation argues that building an opinion on Airbnb externalities on local communities is a complex matter, as long as, conversely to urban markets, the platform effects in marginal economic areas are positive and act as endogenous growth mechanisms (see chapter 4).

References – Conclusion

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Appendix A1 – Chapter 1

Appendix A1.1. Airbnb vs HomeAway (VRBO) within the Italian Market: main metrics of diffusion.

	AB Stock / HA Stock	AB Rn / HA Rn	AB Res / HA Res
Mean	2,95	5,43	7,62
Standard Dev.	2,74	8,41	7,44
Min	0,22	0,14	0,28
5th Perc.	1,16	1,25	1,98
10th Perc.	1,33	1,64	2,39
25th Perc.	1,71	2,45	3,46
Median	2,36	3,87	5,46
75th Perc.	3,38	6,41	9,04
Max	59,00	362,00	146,00

Notes:

e) AB = Airbnb, HA = HomeAway (today VRBO)
f) Stock = Number of Active Properties in sub-market *p* at time *t*
g) Rn = Reserved Nights in sub-market *p* at time *t*
h) Res = Number of Reservations in sub-market *p* at time *t*
i) Data spans within 105 Italian provinces (sub-market *p*) and 30 months from June 2017 to December 2019 (time *t*) because of restrictions on HomeAway dataset.

Appendix A1.2. Derivation of Equation 4 (section 1.3.1.)

Starting from the definition of entrant suppliers' utility in Equation 2 (section 3.1.) it is possible to define δ^{S}_{ipt} as:

$$\delta^{S}_{itp} = \alpha + \beta \ln D_{tpk} + \gamma_1 \mathrm{AvgRent}_{pt} + \gamma_2 \mathrm{PercLux}_{pt} + \gamma_3 \ln \mathrm{GDPc}_{pt} + \gamma_4 \mathrm{MFF}_{pt} + \gamma_5 MFF^2_{pt} + \eta^{S}_{p} + \tau^{S}_{t} + \xi^{S}_{ipt}$$

(Eq. A1.2.1.)

Such that it is possible to rewrite entrant suppliers' utility as:

$$U^{S}_{itp} = \delta^{S}_{itp} + \varepsilon^{S}_{ipt}$$

(Eq. A1.2.2.)

A listing *i* joins Airbnb in sub-market *p* at time *t* if the utility of joining is greater than the utility of not joining:

$$U^{S}_{ipt} > U^{S,\text{not join}}_{ipt}$$

(Eq. A1.2.3.)

Such that the probability of joining is defined as follows:

$$PR^{S,join}\left[U^{S}_{itp} > U^{S,join}_{itp}\right] = PR^{S,join}\left[\delta^{S}_{itp} + \varepsilon^{S}_{itp} > \delta^{S,join}_{itp} + \varepsilon^{S,not\,join}_{itp}\right] = PR^{S,join}[\varepsilon^{S,not\,join}_{itp} - \varepsilon^{S}_{itp} < \delta^{S}_{itp} - \delta^{S,not\,join}_{itp}]$$

(Eq. A1.2.4.)

Thus, under the assumption that the error term ε^{S}_{ipt} follows an Extreme Value Type 1 distribution, the probability of joining is computed as:

$$PR^{S,join}_{ipt} = \frac{1}{1 + e^{-(\delta^{S}_{ipt} - \delta^{S,not\,join}_{ipt})}}$$

(Eq. A1.2.5.)

Assuming that the utility of not joining Airbnb is normalized to zero ($\delta^{S,\text{not join}}_{itp} = 0$) the probabilities of joining and not joining are defined in Equation 4 (section 3.1.):

$$PR^{S,join}_{ipt} = \frac{1}{1 + e^{-(\delta^{S}_{ipt})}} = \frac{e^{\delta^{S}_{ipt}}}{1 + e^{(\delta^{S}_{ipt})}}$$
$$PR^{S,\text{not join}}_{ipt} = 1 - PR^{S,JOIN}_{ipt} = \frac{1}{1 + e^{(\delta^{S}_{ipt})}}$$

(Eq. 4 – Section 1.3.1.)

Appendix A1.3. Derivation of Equation 9 (section 1.3.2.)

Starting from the definition of visitors' utility in Equation 8 (section 3.2.) it is possible to define δ^{D}_{jpt} as:

$$\delta^{D}_{jpt} = \lambda + \rho \ln S_{pt} + \varphi_1 SharePart_{pt} + \varphi_2 ADR_{pt} + \varphi_3 E_{pt} + \eta^{D}_{p} + \tau^{D}_{t} + \xi^{D}_{jtp}$$

(Eq. A1.3.1)

Such that it is possible to rewrite entrant suppliers' utility as:

$$U^{D}_{jtp} = \delta^{D}_{jtp} + \varepsilon^{D}_{jpt}$$

(Eq. A1.3.2.)

A visitor *j* uses Airbnb in sub-market *p* at time *t* (i.e., makes a reservation) if the utility of reserving a night on the platform is greater than the utility of not using the platform:

$$U^{D}_{jpt} > U^{D,\text{not use}}_{jpt}$$

(Eq. A1.3.3.)

Such that the probability of using Airbnb platform is defined as follows:

$$PR^{D,use}\left[U^{D}_{jtp} > U^{D,use}_{jtp}\right] = PR^{D,use}\left[\delta^{D}_{jtp} + \varepsilon^{D}_{jtp} > \delta^{D,use}_{jtp} + \varepsilon^{D,\text{not use}}_{jtp}\right] = PR^{S,use}\left[\varepsilon^{D,\text{not use}}_{jtp} - \varepsilon^{D}_{jtp} < \delta^{D}_{jtp} - \delta^{D,\text{not use}}_{jtp}\right]$$

(Eq. A1.3.4.)

Thus, under the assumption that the error term ε^{D}_{jpt} follows an Extreme Value Type 1 distribution, the probability of using Airbnb is computed as:

$$PR^{D,use}_{jpt} = \frac{1}{1 + e^{-(\delta^{D}_{jpt} - \delta^{D,\text{not use}}_{jpt})}}$$

(Eq. A1.3.5.)

Assuming that the utility of not using Airbnb is normalized to zero ($\delta^{D,\text{not use}}_{jtp} = 0$) the probabilities of using and not using Airbnb are defined in Equation A3.6:

$$PR^{D,use}_{jpt} = \frac{1}{1 + e^{-(\delta^{D}_{jpt})}} = \frac{e^{\delta^{D}_{jpt}}}{1 + e^{(\delta^{D}_{jpt})}}$$

$$PR_{jpt}^{D,not\ use} = 1 - PR_{jpt}^{D,use} = \frac{1}{1 + e^{(\delta_{jpt}^{D})}}$$

(Eq. A1.3.6.)

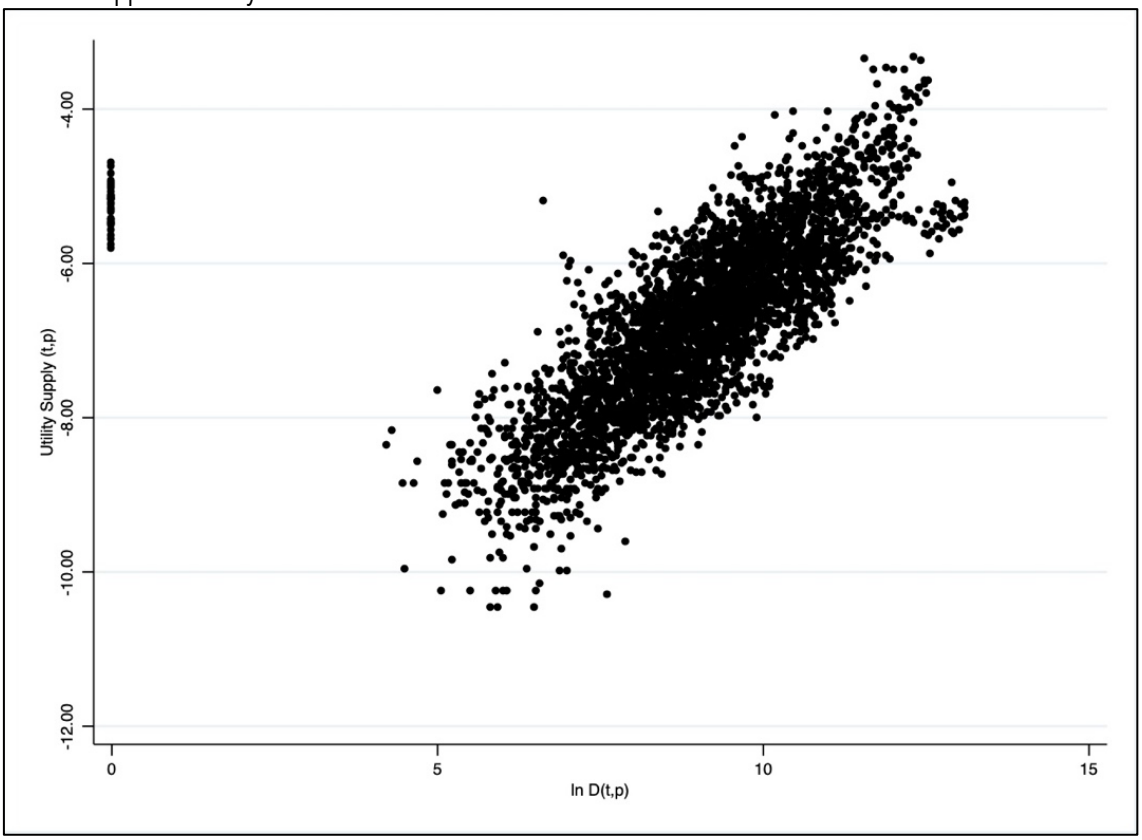
Finally, the demand model equation to be estimated is reported in Equation 9 (section 3.2.):

$$\ln\left(e^{\delta_{itp}^{S}}\right) = \ln\left(\frac{\frac{n_{tp}^{S}}{M_{tp}^{S}}}{\frac{M_{tp}^{S} - n_{tp}^{S}}{M_{tp}^{S}}}\right) = \delta_{itp}^{S}$$
$$= \alpha + \beta \ln D_{tpk} + \gamma_1 AvgRent_{pt} + \gamma_2 PercLux_{pt} + \gamma_3 \ln GDPc_{pt} + \gamma_4 MFF_{pt}$$
$$+ \gamma_5 MFF_{pt}^{2} + \eta_{p}^{S} + \tau_{t}^{S} + \xi_{ipt}^{S}$$

(Eq. 9 – Section 1.3.2.)

Appendix A1.4. Suppliers' Utility vs Demand / Visitors' Utility vs Supply

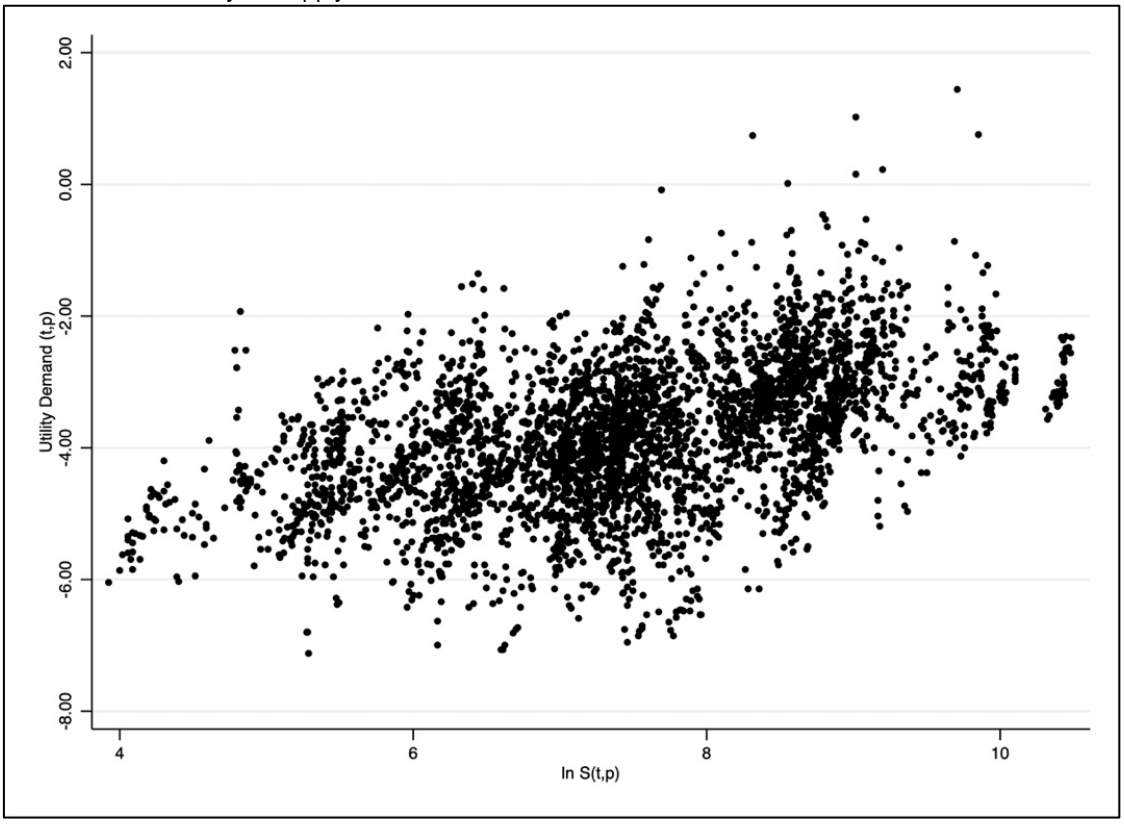
A1.4.1. Suppliers' Utility vs Demand



Notes:

a) $k = 3$ (see Section 4.2.2.)

A1.4.2. Visitors' Utility vs Supply



Appendix A1.5. First stage regressions.

	$Y = \ln D_{ptk}$		$Y = \ln S_{pt}$
$\ln Dha_{ptk}$	0.364***	$\ln Sha_{pt}$	0.310***
	(0.045)		(0.018)
$AvgRent_{pt}$	0.027	ADR_{pt}	-0.000*
	(0.081)		(0.000)
$ShareLux_{pt}$	-0.690	$SharePart_{pt}$	-0.775
	(0.447)		(0.500)
$\ln GDPc_{pt}$	1.364**		
	(0.432)		
MFF_{pt}	0.085***		
	(0.010)		
MFF^2_{pt}	-0.000***		
	(0.000)		
Constant	-12.525**	Constant	5.576***
	(4.337)		(0.127)
SE	Robust		Robust
NUTS2*QuarterFE	no	NUTS2*QuarterFE	yes
MonthFE	yes	MonthFE	yes
IndividualFE	yes	IndividualFE	yes
Observations	2,940	Observations	3,255
Individuals	105	Individuals	105
Overall R2	0.786	Overall R2	0.885
Within R2	0.981	Within R2	0.691
Between R2	0.750	Between R2	0.902
AIC	-5,840.979	AIC	-8,675.837
BIC	-5,739.214	BIC	-8,316.648

Notes:

a) Robust standard errors employed.

b) In demand first stage, k = 3 (see section 1.4.2.2.)

Appendix A1.6. Descriptive statistics for r^D_{ptk} and r^S_{pt}.

	$r^D_{ptk=3}$	r^S_{pt}
Mean	0.000	0.000
Standard Dev.	0.089	0.063
Min	-0.449	-0.749
25th Perc.	-0.055	-0.034
Median	0.008	0.005
75th Perc.	0.065	0.034
Max	0.274	0.375

Appendix A1.7. Correlation Matrixes

A1.7.1. Supply Side Model

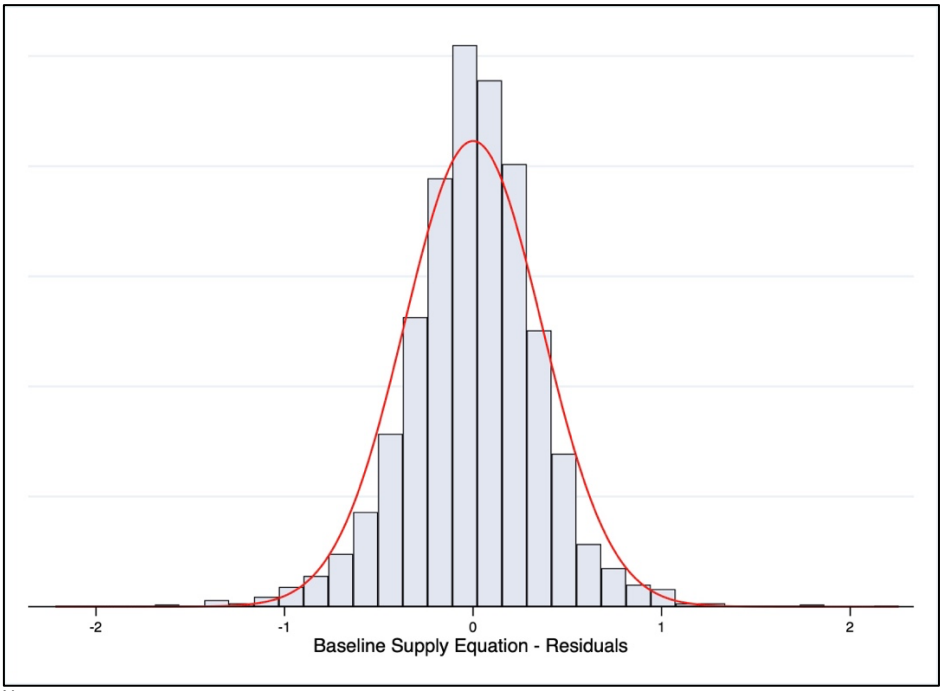
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
δ^{S}_{pt} [1]	1.000						
$lnD_{ptk=3}$ [2]	0.766	1.000					
$lnDha_{ptk=3}$ [3]	0.766	0.930	1.000				
$AvgRent_{pt}$ [4]	0.348	0.313	0.301	1.000			
$PercLux_{pt}$ [5]	0.152	0.190	0.103	-0.055	1.000		
$lnGDPc_{pt}$ [6]	0.205	0.263	0.174	0.357	-0.367	1.000	
MFF_{pt} [7]	0.433	0.757	0.697	0.149	0.143	0.172	1.000

A1.7.2. Demand Side Model

	[1]	[2]	[3]	[4]	[5]
δ^{D}_{pt} [1]	1.000				
lnS_{pt} [2]	0.474	1.000			
$lnSha_{pt}$ [3]	0.500	0.938	1.000		
$SharePart_{pt}$ [4]	0.336	0.152	0.226	1.000	
ADR [5]	0.246	0.487	0.587	0.291	1.000

Appendix A1.8. Baseline Suppliers Utility Model – diagnostic plots.

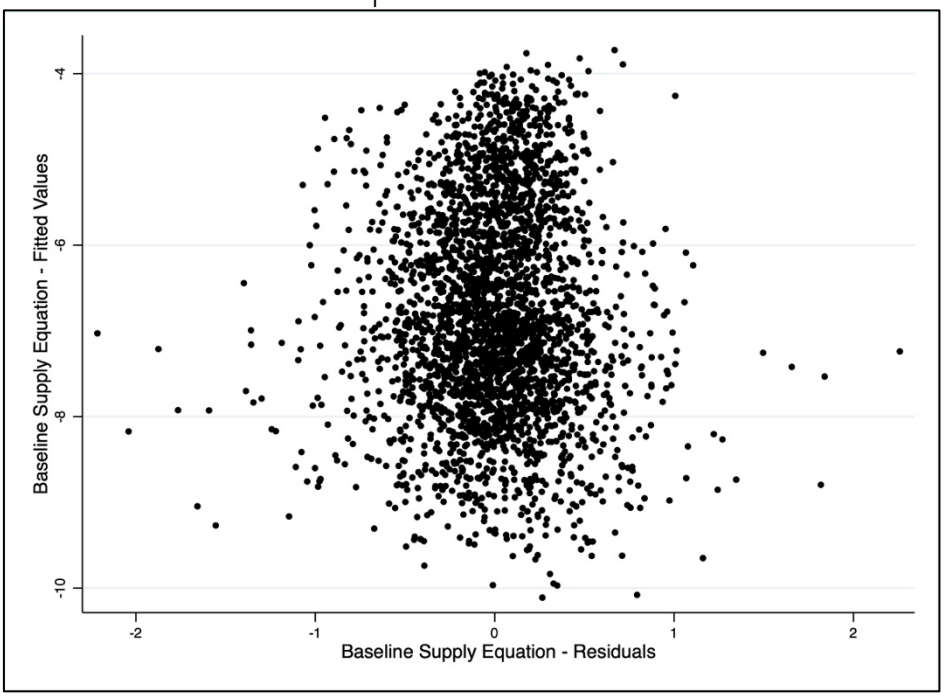
A1.8.1. Residuals distribution.



Notes:

a) Residuals are computed from model M6 in Table 1.3.
b) Similar results are obtained for models M5 (standard OLS), and M7 (quadratic form for the control function) and are available upon request to the author.

A1.8.2. Residuals vs Fitted Values plot.

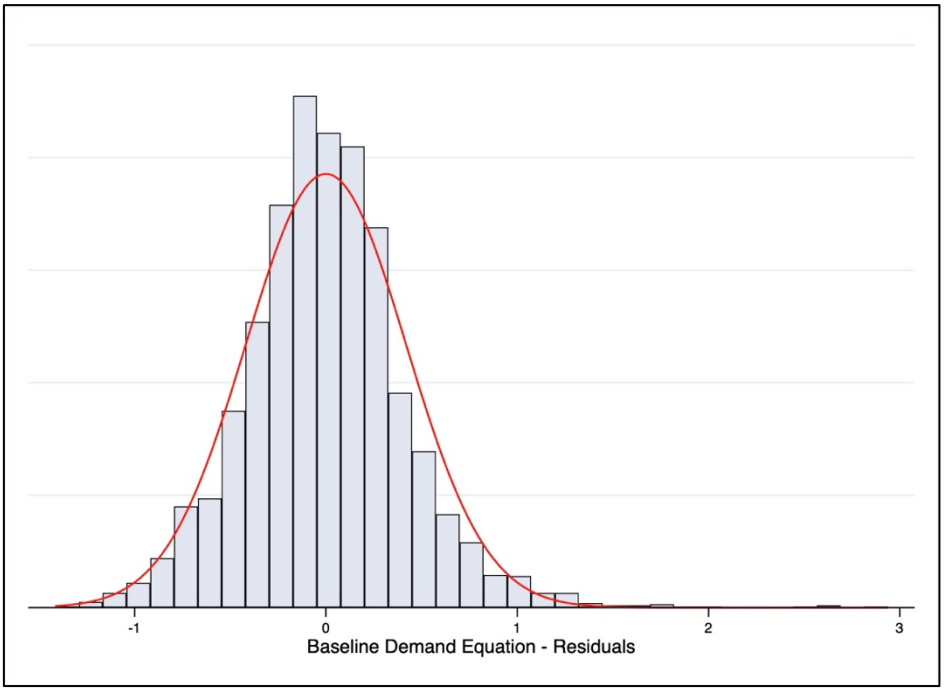


Notes:

a) Residuals and fitted values are computed from model M6 in Table 1.3.
b) Similar results are obtained for models M5 (standard OLS), and M7 (quadratic form for the control function) and are available upon request to the author.

Appendix A1.9. Baseline Visitors Utility Model – diagnostic plots.

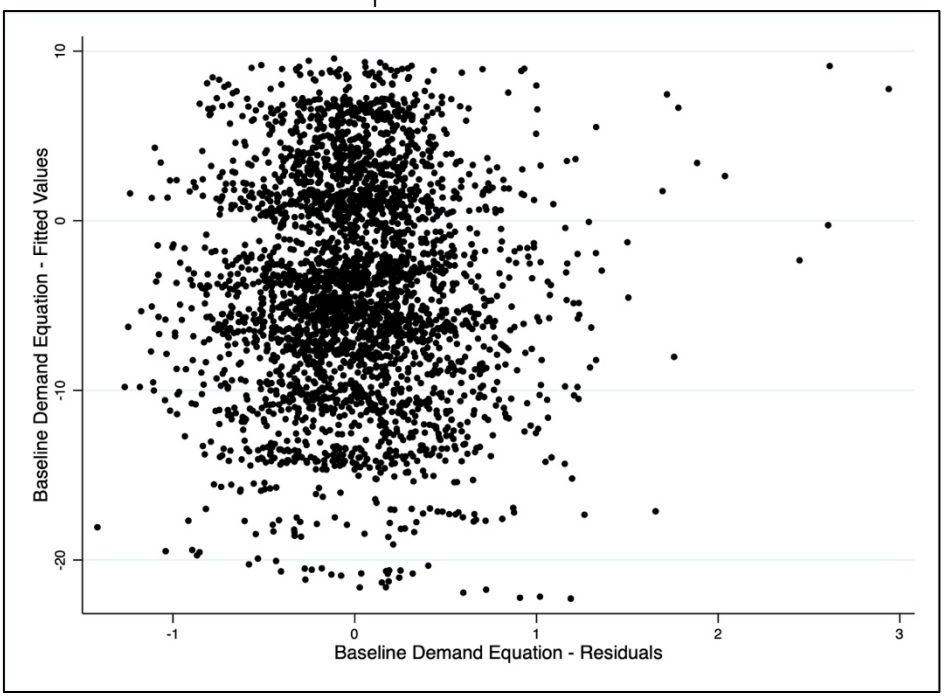
A1.9.1. Residuals distribution.



Notes:

a) Residuals are computed from model M6 in Table 1.4.
b) Similar results are obtained for models M5 (standard OLS), and M7 (quadratic form for the control function) and are available upon request to the author.

A1.9.2. Residuals vs Fitted Values plot.



Notes:

a) Residuals and fitted values are computed from model M6 in Table 1.4.
b) Similar results are obtained for models M5 (standard OLS), and M7 (quadratic form for the control function) and are available upon request to the author.

Appendix A1.10. Baseline Models estimated through SURE regression modeling.

	Obs	Params	RMSE	R2	chi2	P>chi2
Supply Model - Eq. 6	2,934	18	0.364	0.428	2202.690	0.000
Demand Model - Eq. 9	2,934	75	0.366	0.592	4263.510	0.000

		Coefficient	Standard Error
Supply Equation	MonthFE	yes	
	IndividualFE	yes	
	MFF_{pt}	-0.070**	(0.020)
	MFF^2_{pt}	0.000	(0.000)
	$AvgRent_{pt}$	-0.346**	(0.123)
	$PercLux_{pt}$	0.998	(0.659)
	$lnGDPc_{pt}$	-2.761***	(0.672)
	r^D_{pt}	-0.163	(0.165)
	$lnD_{ptk=3}$	0.830***	(0.146)
	Constant	18.960**	(6.710)
Demand Equation	IndividualFE	yes	
	MonthFE	yes	
	NUTS2*QuarterFE	yes	
	$SharePart_{pt}$	17.890***	(1.160)
	ADR_{pt}	0.000	(0.000)
	r^S_{pt}	-2.482***	(0.145)
	lnS_{pt}	4.370***	(0.083)
	Constant	-37.902***	(0.662)

Notes:

a) *** p<0.001, ** p<0.01, * p<0.05, + p<0.10

b) The model tested into the SURE equation employ a linear control function. Similar results are obtained for standard OLS model and models including a quadratic control function.

c) The correlation between the error terms is 0.031, and the Chi^2 statistics of the Breusch–Pagan test of independence is 2.789, significant at the 90% confidence level (p-value = 0.095).

Appendix A1.11. Baseline Supply Model using AR(1) error term.

	M1	M2	M3	M4	M5	M6	M7
MFF_{pt}		0.006	0.037***	0.036***	-0.057**	-0.073*	-0.074*
		(0.008)	(0.008)	(0.008)	(0.017)	(0.029)	(0.029)
MFF^2_{pt}		-0.000	-0.000***	-0.000***	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$lnGDPc_{pt}$			-1.046***	-1.021***	-0.927***	-0.921***	-0.909***
			(0.090)	(0.103)	(0.135)	(0.136)	(0.135)
$AvgRent_{pt}$				-0.161	-0.214	-0.225	-0.231
				(0.121)	(0.175)	(0.176)	(0.176)
$PercLux_{pt}$				0.332	1.025	1.153	1.168
				(0.776)	(0.856)	(0.875)	(0.876)
$lnD_{ptk=3}$					0.724***	0.848***	0.854***
					(0.104)	(0.204)	(0.204)
$r^D_{ptk=3}$						-0.157	-0.087
						(0.222)	(0.225)
$(r^D_{ptk=3})^2$							2.024*
							(0.959)
Constant	-7.156***	-7.485***	1.597*	1.807**	-0.045	-0.196	-0.347
	(0.021)	(0.282)	(0.643)	(0.655)	(0.858)	(0.873)	(0.868)
Error Term	AR(1)	AR(1)	AR(1)	AR(1)	AR(1)	AR(1)	AR(1)
MonthFE	yes	yes	yes	yes	yes	yes	yes
IndividualFE	yes	yes	yes	yes	yes	yes	yes
Observations	3,665	3,665	3,665	3,665	2,829	2,829	2,829
Individuals (p)	105	105	105	105	105	105	105
Overall R2	0.090	0.099	0.016	0.003	0.353	0.389	0.386
Within R2	0.371	0.372	0.395	0.396	0.364	0.364	0.365
Between R2	0.002	0.324	0.034	0.103	0.344	0.390	0.387
AIC	3,522.015	3,521.610	3,386.129	3,388.080	2,226.515	2,227.978	2,225.600
BIC	3,596.494	3,608.502	3,479.227	3,493.592	2,333.574	2,340.984	2,344.554

Notes:

c) *** p<0.001, ** p<0.01, * p<0.05, + p<0.10

d) M5 uses traditional OLS, while M6 and M7 employ the two-stage approach including first stage residuals.

Appendix A1.12. Baseline Demand Model using AR(1) error term.

	M1	M2	M3	M4	M5	M6	M7
$SharePart_{pt}$			0.905	1.018	7.530***	11.509***	11.676***
			(1.941)	(1.937)	(1.777)	(1.922)	(1.947)
ADR_{pt}				0.002***	0.002***	0.002***	0.002***
				(0.000)	(0.000)	(0.000)	(0.000)
lnS_{pt}					2.940***	4.773***	4.761***
					(0.154)	(0.221)	(0.222)
r^S_{pt}						-3.208***	-3.258***
						(0.287)	(0.296)
$(r^S_{pt})^2$							-0.585
							(0.810)
Constant	-3.207***	-3.237***	-3.314***	-3.490***	-26.343***	-40.614***	-40.540***
	(0.006)	(0.006)	(0.022)	(0.022)	(0.308)	(0.503)	(0.503)
Error Term	AR(1)	AR(1)	AR(1)	AR(1)	AR(1)	AR(1)	AR(1)
NUTS2*QuarterFE	no	yes	yes	yes	yes	yes	yes
MonthFE	yes	yes	yes	yes	yes	yes	yes
IndividualFE	yes	yes	yes	yes	yes	yes	yes
Observations	3,675	3,675	3,675	3,675	3,675	3,150	3,150
Individuals (p)	105	105	105	105	105	105	105
Overall R2	0.056	0.066	0.098	0.134	0.273	0.261	0.262
Within R2	0.179	0.211	0.211	0.215	0.293	0.286	0.286
Between R2	.	0.008	0.085	0.160	0.373	0.376	0.377
AIC	2,127.216	2,096.508	2,098.276	2,082.234	1,962.470	1,681.081	1,682.740
BIC	2,201.727	2,543.579	2,551.556	2,541.723	2,428.168	2,141.273	2,148.988

Notes:

a) *** p<0.001, ** p<0.01, * p<0.05, + p<0.10

b) M5 uses traditional OLS, while M6 and M7 employ the two-stage approach including first stage residuals.

Appendix A1.13. Fraction of market potential for suppliers, using 50% of starting market potential.

	M1	M2	M3	M4	M5	M6	M7
MFF_{pt}		0.022**	0.022*	0.021*	-0.062***	-0.070*	-0.071+
		(0.008)	(0.009)	(0.009)	(0.016)	(0.034)	(0.037)
MFF^2_{pt}		-0.000*	-0.000*	-0.000*	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$lnGDPc_{pt}$			0.028	0.020	-1.792	-1.859	-1.828
			(1.196)	(1.141)	(1.180)	(1.227)	(1.220)
$AvgRent_{pt}$				-0.221*	-0.390***	-0.395***	-0.396***
				(0.095)	(0.113)	(0.115)	(0.114)
$PercLux_{pt}$				0.207	0.960	1.022	1.036
				(0.542)	(0.840)	(0.865)	(0.874)
$lnD_{ptk=3}$					0.674***	0.739**	0.748**
					(0.077)	(0.223)	(0.241)
$r^D_{ptk=3}$						-0.082	-0.058
						(0.270)	(0.237)
$(r^D_{ptk=3})^2$							0.504
							(1.540)
Constant	-6.373***	-7.467***	-7.748	-6.937	10.668	11.291	10.960
	(0.020)	(0.390)	(11.857)	(11.129)	(11.482)	(11.966)	(11.883)
SE	Robust	Robust	Robust	Robust	Robust	Robust	Robust
MonthFE	yes	yes	yes	yes	yes	yes	yes
IndividualFE	yes	yes	yes	yes	yes	yes	yes
Observations	3,771	3,771	3,771	3,771	2,934	2,934	2,934
Individuals (p)	105	105	105	105	105	105	105
Overall R2	0.077	0.090	0.092	0.004	0.087	0.103	0.109
Within R2	0.437	0.440	0.440	0.441	0.431	0.431	0.431
Between R2	0.006	0.196	0.233	0.131	0.064	0.081	0.087
AIC	3,718.612	3,703.356	3,705.354	3,703.409	2,453.952	2,455.707	2,456.997
BIC	3,787.198	3,784.412	3,792.645	3,803.171	2,555.682	2,563.421	2,570.696

Notes:

a) Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.10

b) M5 uses traditional OLS, while M6 and M7 employ the two-stage approach including first stage residuals.

Appendix A1.14. Fraction of market potential for suppliers, using 60% of starting market potential.

	M1	M2	M3	M4	M5	M6	M7
MFF_{pt}		0.025**	0.026**	0.025**	-0.056***	-0.067*	-0.068+
		(0.007)	(0.008)	(0.008)	(0.014)	(0.034)	(0.036)
MFF^2_{pt}		-0.000**	-0.000**	-0.000**	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$lnGDPc_{pt}$			-0.578	-0.583	-2.352**	-2.434**	-2.408**
			(0.785)	(0.744)	(0.846)	(0.906)	(0.895)
$AvgRent_{pt}$				-0.186*	-0.352***	-0.359***	-0.359***
				(0.080)	(0.098)	(0.099)	(0.099)
$PercLux_{pt}$				0.150	0.915	0.992	1.003
				(0.538)	(0.842)	(0.866)	(0.875)
$lnD_{ptk=3}$					0.676***	0.755***	0.763**
					(0.077)	(0.221)	(0.238)
$r^D_{ptk=3}$						-0.101	-0.080
						(0.267)	(0.234)
$(r^D_{ptk=3})^2$							0.428
							(1.527)
Constant	-6.579***	-7.790***	-2.007	-1.328	15.766+	16.531+	16.249+
	(0.020)	(0.357)	(7.851)	(7.352)	(8.349)	(8.969)	(8.837)
SE	Robust	Robust	Robust	Robust	Robust	Robust	Robust
MonthFE	yes	yes	yes	yes	yes	yes	yes
IndividualFE	yes	yes	yes	yes	yes	yes	yes
Observations	3,771	3,771	3,771	3,771	2,934	2,934	2,934
Individuals (p)	105	105	105	105	105	105	105
Overall R2	0.082	0.091	0.037	0.006	0.079	0.098	0.102
Within R2	0.439	0.442	0.442	0.443	0.430	0.430	0.430
Between R2	0.007	0.103	0.032	0.138	0.057	0.078	0.082
AIC	3,692.503	3,675.703	3,676.774	3,676.568	2,436.230	2,437.859	2,439.344
BIC	3,761.089	3,756.759	3,764.065	3,776.330	2,537.960	2,545.573	2,553.042

Notes:

a) Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.10

b) M5 uses traditional OLS, while M6 and M7 employ the two-stage approach including first stage residuals.

Appendix A1.15. Full regression output, modified supply model.

	M1	M2	M3
MFF_{pt}	-0.065+	-0.064+	-0.064+
	(0.034)	(0.033)	(0.034)
MFF^2_{pt}	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
$lnGDPc_{pt}$	-2.719**	-2.657**	-2.659**
	(0.810)	(0.791)	(0.786)
$AvgRent_{pt}$	-0.333***	-0.343***	-0.327***
	(0.091)	(0.091)	(0.086)
$PercLux_{pt}$	0.938	0.937	0.858
	(0.861)	(0.854)	(0.830)
$r^D_{ptk=3}$	-0.128	-0.082	-0.096
	(0.288)	(0.264)	(0.283)
$lnD_{ptk=3}$	0.771***	0.783***	0.790***
	(0.221)	(0.223)	(0.228)
$lnD_{ptk=3} * SI_p$	0.007		0.047
	(0.075)		(0.093)
$lnD_{ptk=3} * DI_p$		-0.073	-0.096
		(0.080)	(0.100)
Constant	18.610*	18.229*	18.142*
	(8.035)	(7.934)	(7.851)
SE	Robust	Robust	Robust
MonthFE	yes	yes	yes
IndividualFE	yes	yes	yes
Observations	2,934	2,934	2,934
Individuals (p)	105	105	105
Overall R2	0.109	0.055	0.082
Within R2	0.428	0.428	0.428
Between R2	0.090	0.037	0.063
AIC	2,434.262	2,432.483	2,433.756
BIC	2,547.961	2,546.181	2,553.439

Notes:

a) Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.10.

Appendix A1.16. Full regression output, modified demand model.

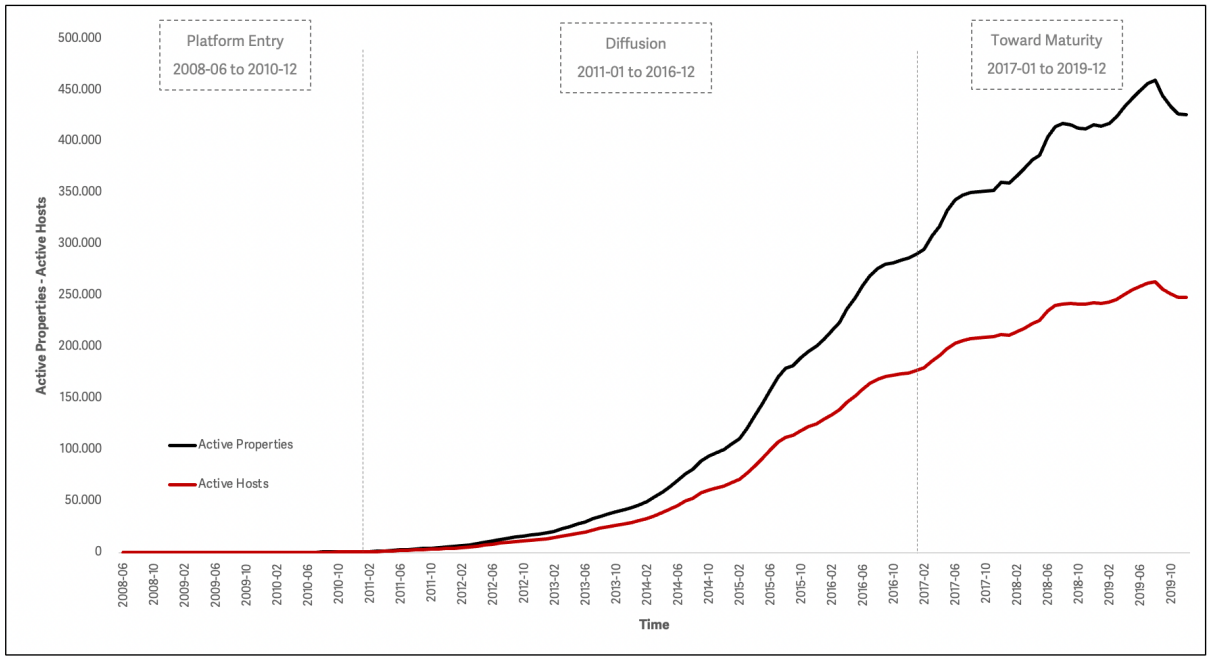
	M1	M2	M3
$SharePart_{pt}$	21.044***	22.914***	22.164***
	(2.367)	(2.366)	(2.232)
ADR_{pt}	0.002*	0.003*	0.002*
	(0.001)	(0.001)	(0.001)
r^{S}_{pt}	-2.496***	-2.502***	-2.267***
	(0.332)	(0.348)	(0.365)
lnS_{pt}	3.680***	5.543***	4.800***
	(0.345)	(0.497)	(0.407)
$lnS_{pt} * SI_{p}$	2.197***		2.840***
	(0.492)		(0.614)
$lnS_{pt} * DI_{p}$		-1.264+	-2.405***
		(0.712)	(0.571)
Constant	-42.446***	-41.283***	-41.961***
	(1.454)	(1.637)	(1.297)
SE	Robust	Robust	Robust
NUTS2*QuarterFE	yes	yes	yes
MonthFE	yes	yes	yes
IndividualFE	yes	yes	yes
Observations	3,255	3,255	3,255
Individuals (p)	105	105	105
Overall R2	0.185	0.310	0.217
Within R2	0.628	0.622	0.633
Between R2	0.273	0.449	0.322
AIC	3,631.529	3,682.383	3,586.337
BIC	4,002.894	4,053.747	3,963.789

Notes:

a) Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.10.

Appendix A2 – Chapter 2

Appendix A2.1. Airbnb Supply Diffusion and Empirical Setting of the research.



Notes. The chart shows the various stages of the diffusion of Airbnb supply, which can be catalogued as:

a) "Platform Entry" since 2008-06 (when the first Airbnb has opened within the Italian territory) to 2010-12;
b) "Diffusion" (in the sense of *disruption*) from 2011-01 to 2016-12;
c) "Toward Maturity", which is the period analuyzed in the study.

The last period is far from the first inception of Airbnb within the Italian territory (indeed in all sub-markets analyzed Airbnb has already entered), and it counts about 300.000 properties at the beginning of the study period (see Table 2.1. for the exact statistics). Within the sample it is possible to observe either a significant growth of the demand (+271% reserved nights between January 2017 and December 2019) and an adjustment of the supply (+46% stock of active properties from January 2017 to December 2019), with significant variations within the panel units.

Appendix A2.2. Explained Variance Decomposition: Shapley Values.

	Small Scale Entrepreneurs' entries		Large Scale Entrepreneurs' entries	
	Shapley Value Estimate	Per cent Estimate	Shapley Value Estimate	Per cent Estimate
Group 1	0,277	30,24%	0,212	26,34%
Group 2	0,116	12,66%	0,122	15,16%
Group 3	0,239	26,09%	0,233	28,94%
Group 4	0,098	10,70%	0,079	9,81%
Group 5	0,186	20,31%	0,159	19,75%
TOTAL	0,916	100,00%	0,805	100,00%

Notes:

- Group 1 = ln $Y_{p,t-1}$ (Lagged Dependent Variable)
- Group 2 = $ConcentrationProp_{p,t-1}$, $ConcentrationProp^2_{p,t-1}$ (Concentration)
- Group 3 = ln $MarketClimate^3_{p,t}$ (Demand)
- Group 4 = ln $UnoccupiedDwellings_p$, $UnemplRate_{p,t}$, $HighRangeSpecialized_p$ (Costs)
- Group 5 = ln $AVGRent_{p,t}$, ln $Altitude_p$, $PercSeasideMun_p$, ln$BedHotels_p$, MonthFe, Time Trend (Control Variables)

Shapley values estimated according to a pooled-OLS, similar to the Random Effects and GMM-SYS estimate in Table 2.5.

Appendix A2.3. Robustness Check #1: Different Thresholds Defining Entrepreneurs.

	SSE[1] RE	SSE[1] GMM-SYS	SSE[1-4] RE	SSE [1-4]GMM-SYS	LSE [5-10] RE	LSE [5-10] GMM-SYS
ln Y (p, t-1)	0.4366***	0.1995***	0.4167***	0.1459**	0.2494***	0.4340***
	(0.044)	(0.064)	(0.044)	(0.057)	(0.028)	(0.097)
$ConcentrationProp_{pt-1}$	0.0134	0.0107	0.0064	0.0084	0.1590***	0.1102***
	(0.023)	(0.043)	(0.022)	(0.040)	(0.035)	(0.039)
$ConcentrationProp_{pt-1}$^2	0.0013	0.0024	0.0016	0.0024	-0.0085***	-0.0057**
	(0.001)	(0.003)	(0.001)	(0.003)	(0.002)	(0.002)
ln $MarketClimate^3_{pt}$	0.3241***	0.4668***	0.3458***	0.5062***	0.2960***	0.2080***
	(0.031)	(0.048)	(0.031)	(0.044)	(0.031)	(0.052)
ln $UnoccupiedDwellings_p$	0.1204***	0.1664***	0.1177***	0.1640***	0.0106	0.0361
	(0.025)	(0.042)	(0.024)	(0.044)	(0.042)	(0.063)
$UnemplRate_{pt}$	1.0586***	1.5738***	1.1704***	1.6793***	1.8975***	0.4260
	(0.314)	(0.576)	(0.323)	(0.550)	(0.431)	(1.608)
$HighRangeSpecialized_p$	0.0363	0.0514	0.0297	0.0531	0.0811*	0.1011
	(0.026)	(0.044)	(0.026)	(0.047)	(0.043)	(0.072)
ln $AVGRent_{pt}$	-0.0159	-0.0226	-0.0232	-0.0365	-0.0348	-0.0612
	(0.031)	(0.057)	(0.031)	(0.053)	(0.053)	(0.070)
ln $Altitude_p$	0.0529***	0.0729***	0.0538***	0.0789***	0.0052	0.0202
	(0.012)	(0.024)	(0.012)	(0.021)	(0.021)	(0.030)
$PercSeasideMunicipalities_p$	0.1547**	0.2352*	0.1649**	0.2624*	-0.3342***	-0.0786
	(0.069)	(0.131)	(0.068)	(0.138)	(0.110)	(0.220)
ln $BedHotels_p$	0.0576***	0.0850***	0.0576***	0.0911***	0.0642***	0.0460*
	(0.016)	(0.027)	(0.015)	(0.026)	(0.021)	(0.026)
Constant	-3.2916***	-4.6830***	-3.4304***	-4.9459***	-2.9216***	-2.3782***
	(0.342)	(0.479)	(0.335)	(0.455)	(0.394)	(0.576)
N	3,060	3,060	3060	3060	3060	3060
Overall R2	0.9168		0.9159		0.7142	
# Instruments		109		109		111
# Instruments / p		1,07		1,07		1,09
# Instruments / N		0,04		0,04		0,04
AR (1)		-5.15***		-5.25***		-6.09***
AR (2)		2.89***		3.10***		3.05***
AR (3)		-2.58**		-3.26***		0.90
AR (4)		0.56		1.42		/
Hansen Test J (p-value)		100.30 (0.123)		99.44 (0.120)		91.95 (0.311)
Maximum Bell Shaped Curve						9.73
Std. Error Maximum						0.89

Notes:

a) Robust standard errors are in parenthesis. *** p<0.01; ** p<0.05; * p<0.10.

b) In GMM-SYS estimates, the instrument set is curtailed according to the Arellano-Bond AR (#) Test. $e^n_{SSEpt-1}$ is instrumented with lags [t-4;t-5]. $e^n_{LSEpt-1}$ is instrumented with lags [t-3;t-4]. GMM models adopt two-step estimations and have been corrected with the Windmeijer (2005) covariance matrix for finite samples.

Appendix A2.4a. Robustness Check #2a: Different specification of $MarketClimate_{pt}$ employing $DemandFuture_{pt}$.

	SSE [1-2 listings]		SSE [1-3 listings]		LSE [1-4 listings]		LSE [3-10 listings]		LSE [4-10 listings]		LSE [5-10 listings]	
	RE	GMM-SYS	RE	GMM-SYS	RE	GMM-SYS	RE	GMM-SYS	RE	GMM-SYS	RE	GMM-SYS
ln Y (p, t-1)	0.3812***	0.1304**	0.3737***	0.1107**	0.3720***	0.1061**	0.1899***	0.1107	0.1875***	0.2597***	0.2306***	0.3719***
	(0.045)	(0.052)	(0.045)	(0.053)	(0.045)	(0.050)	(0.024)	(0.071)	(0.027)	(0.071)	(0.028)	(0.088)
$ConcentrationProp_{pt-1}$	0.0098	0.0125	0.0085	0.0166	0.0063	0.0129	0.1007***	0.1326***	0.1461***	0.1282***	0.1605***	0.1097***
	(0.023)	(0.040)	(0.023)	(0.043)	(0.023)	(0.040)	(0.033)	(0.042)	(0.035)	(0.047)	(0.035)	(0.040)
$ConcentrationProp_{pt-1}$^2	0.0021	0.0030	0.0022	0.0028	0.0023	0.0030	-0.0047**	-0.0065**	-0.0072***	-0.0066**	-0.0081***	-0.0052**
	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
ln $DemandFuture_{pt}$	0.3405***	0.4762***	0.3466***	0.4892***	0.3487***	0.4896***	0.4095***	0.4310***	0.3503***	0.3158***	0.2863***	0.2451***
	(0.028)	(0.038)	(0.029)	(0.039)	(0.029)	(0.037)	(0.026)	(0.051)	(0.029)	(0.041)	(0.028)	(0.045)
ln $UnoccupiedDwellings_{p}$	0.1545***	0.2179***	0.1555***	0.2183***	0.1558***	0.2170***	0.0476	0.0572	0.0349	0.0178	0.0339	0.0159
	(0.029)	(0.050)	(0.029)	(0.053)	(0.029)	(0.053)	(0.036)	(0.046)	(0.041)	(0.046)	(0.041)	(0.043)
$UnemplRate_{pt}$	1.2824***	1.8462***	1.2790***	1.8432***	1.3011***	1.7282***	2.8267***	2.8908***	2.4749***	1.9882***	1.9801***	1.7210***
	(0.340)	(0.622)	(0.348)	(0.625)	(0.353)	(0.602)	(0.411)	(0.644)	(0.472)	(0.500)	(0.434)	(0.565)
$HighRangeSpecialized_{p}$	0.0467	0.0662	0.0453	0.0672	0.0431	0.0695	0.0994**	0.1171**	0.1101***	0.1118**	0.0920**	0.0727
	(0.030)	(0.052)	(0.030)	(0.049)	(0.030)	(0.051)	(0.041)	(0.054)	(0.042)	(0.047)	(0.044)	(0.048)
ln $AVGRent_{pt}$	-0.0269	-0.0329	-0.0259	-0.0360	-0.0249	-0.0465	-0.0681	-0.0818	-0.0424	-0.0305	-0.0353	-0.0400
	(0.035)	(0.064)	(0.035)	(0.066)	(0.035)	(0.063)	(0.046)	(0.061)	(0.048)	(0.052)	(0.053)	(0.065)
ln $Altitude_{p}$	0.0547***	0.0762***	0.0540***	0.0821***	0.0516***	0.0742***	0.0169	0.0249	0.0180	0.0278	0.0001	-0.0015
	(0.014)	(0.025)	(0.014)	(0.025)	(0.014)	(0.024)	(0.021)	(0.024)	(0.023)	(0.027)	(0.021)	(0.025)
$PercSeasideMunicipalities_{p}$	0.1739**	0.2587**	0.1749**	0.2566**	0.1761**	0.2754**	-0.1680*	-0.1647	-0.2758**	-0.2382*	-0.3425***	-0.2551**
	(0.071)	(0.120)	(0.070)	(0.130)	(0.071)	(0.127)	(0.093)	(0.133)	(0.113)	(0.139)	(0.109)	(0.115)
ln $BedHotels_{p}$	0.0577***	0.0883***	0.0566***	0.0844***	0.0564***	0.0904***	0.0706***	0.0856***	0.0676***	0.0751***	0.0594***	0.0463**
	(0.018)	(0.029)	(0.019)	(0.031)	(0.018)	(0.030)	(0.022)	(0.029)	(0.022)	(0.028)	(0.021)	(0.023)
Constant	-4.1246***	-5.8141***	-4.1813***	-5.9045***	-4.1975***	-5.8831***	-4.5184***	-4.8981***	-4.0698***	-3.7209***	-3.4041***	-2.7364***
	(0.389)	(0.540)	(0.395)	(0.529)	(0.389)	(0.505)	(0.380)	(0.601)	(0.411)	(0.538)	(0.412)	(0.545)
N	3060	3060	3060	3060	3060	3060	3060	3060	3060	3060	3060	3060
Overall R2	0.9206		0.9204		0.9204		0.8128		0.7536		0.7198	
# Instruments		109		109		109		112		112		112
# Instruments / p		1,07		1,07		1,07		1,10		1,10		1,10
# Instruments / N		0,04		0,04		0,04		0,04		0,04		0,04
AR (1)		-5.55***		-5.36***		-5.55***		-5.83***		-6.59***		-6.12***
AR (2)		3.01***		2.81***		3.09***		1.78*		3.22***		2.86***
AR (3)		-2.75***		-2.75***		-3.08***		-1.04		-0.43		0.76
AR (4)		1.48		1.67*		1.96*		/		/		/
Hansen Test J (p-value)		100.30		99.98		99.20		92.93		86.32		93.78
		(0.123)		(0.128)		(0.139)		(0.339)		(0.531)		(0.317)

Notes:

a) Robust standard errors are in parenthesis. *** p<0.01; ** p<0.05; * p<0.10.

b) In GMM-SYS estimates, the instrument set is curtailed according to the Arellano-Bond AR (#) Test. $e^{n}_{SSEpt-1}$ is instrumented with lags [t-4;t-5]. $e^{n}_{LSEpt-1}$ is instrumented with lags [t-3;t-4]. GMM models adopt two-step estimations and have been corrected with the Windmeijer (2005) covariance matrix for finite samples.

Appendix A2.4b. Robustness Check #2a: Different specification of $MarketClimate_{pt}$ employing $DemandFutureT_{pt}$.

	SSE [1-2 listings]		SSE [1-3 listings]		SSE [1-4 listings]		LSE [3-10 listings]		LSE [4-10 listings]		LSE [5-10 listings]	
	RE	GMM-SYS	RE	GMM-SYS	RE	GMM-SYS	RE	GMM-SYS	RE	GMM-SYS	RE	GMM-SYS
ln Y (p, t-1)	0.4083***	0.1913***	0.4006***	0.1710***	0.3981***	0.1633***	0.2078***	0.1574**	0.1954***	0.2660***	0.2354***	0.3810***
	(0.041)	(0.048)	(0.042)	(0.049)	(0.042)	(0.046)	(0.023)	(0.074)	(0.026)	(0.073)	(0.028)	(0.090)
$ConcentrationProp_{pt-1}$	0.0146	0.0244	0.0131	0.0309	0.0106	0.0254	0.1068***	0.1305***	0.1506***	0.1331***	0.1664***	0.1115***
	(0.023)	(0.040)	(0.023)	(0.042)	(0.022)	(0.040)	(0.033)	(0.038)	(0.034)	(0.043)	(0.035)	(0.039)
$ConcentrationProp_{pt-1}$^2	0.0019	0.0023	0.0019	0.0019	0.0021	0.0022	-0.0049**	-0.0063***	-0.0074***	-0.0067**	-0.0083***	-0.0052**
	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
ln $DemandFutureT_{pt}$	0.3107***	0.4167***	0.3171***	0.4287***	0.3199***	0.4332***	0.3803***	0.3920***	0.3309***	0.2943***	0.2691***	0.2286***
	(0.025)	(0.031)	(0.025)	(0.033)	(0.025)	(0.032)	(0.025)	(0.048)	(0.027)	(0.040)	(0.027)	(0.045)
ln $UnoccupiedDwellings_{p}$	0.1615***	0.2217***	0.1626***	0.2248***	0.1630***	0.2201***	0.0642*	0.0749*	0.0492	0.0317	0.0467	0.0235
	(0.029)	(0.049)	(0.029)	(0.053)	(0.029)	(0.050)	(0.035)	(0.040)	(0.040)	(0.043)	(0.040)	(0.041)
$UnemplRate_{pt}$	1.1968***	1.6388***	1.1953***	1.6081***	1.2195***	1.6694***	2.7227***	2.7730***	2.4215***	2.0042***	1.9345***	1.6739***
	(0.333)	(0.629)	(0.341)	(0.580)	(0.345)	(0.596)	(0.413)	(0.626)	(0.473)	(0.514)	(0.436)	(0.563)
$HighRangeSpecialized_{p}$	0.0527*	0.0700	0.0514*	0.0716	0.0494	0.0741	0.1074***	0.1119**	0.1176***	0.1115***	0.0989**	0.0777*
	(0.030)	(0.056)	(0.030)	(0.050)	(0.030)	(0.048)	(0.041)	(0.053)	(0.042)	(0.043)	(0.044)	(0.046)
ln $AVGRent_{pt}$	-0.0246	-0.0302	-0.0238	-0.0431	-0.0228	-0.0411	-0.0654	-0.0665	-0.0409	-0.0389	-0.0342	-0.0377
	(0.035)	(0.065)	(0.035)	(0.065)	(0.035)	(0.061)	(0.045)	(0.056)	(0.047)	(0.052)	(0.051)	(0.061)
ln $Altitude_{p}$	0.0505***	0.0684***	0.0498***	0.0720***	0.0475***	0.0667***	0.0143	0.0195	0.0158	0.0239	-0.0014	-0.0030
	(0.014)	(0.025)	(0.014)	(0.025)	(0.014)	(0.024)	(0.020)	(0.023)	(0.022)	(0.025)	(0.020)	(0.024)
$PercSeasideMunicipalities_{p}$	0.1611**	0.2341*	0.1623**	0.2263*	0.1640**	0.2384*	-0.1717*	-0.1903*	-0.2787**	-0.2393*	-0.3461***	-0.2476**
	(0.069)	(0.121)	(0.068)	(0.129)	(0.069)	(0.126)	(0.090)	(0.114)	(0.110)	(0.128)	(0.108)	(0.110)
ln $BedHotels_{p}$	0.0538***	0.0836***	0.0526***	0.0820***	0.0522***	0.0868***	0.0688***	0.0794***	0.0660***	0.0701***	0.0597***	0.0475**
	(0.019)	(0.031)	(0.019)	(0.031)	(0.019)	(0.030)	(0.022)	(0.029)	(0.023)	(0.025)	(0.021)	(0.022)
Constant	-3.8617***	-5.2725***	-3.9172***	-5.3705***	-3.9382***	-5.3756***	-4.3247***	-4.6054***	-3.9436***	-3.5225***	-3.3148***	-2.6199***
	(0.367)	(0.502)	(0.373)	(0.511)	(0.367)	(0.473)	(0.370)	(0.611)	(0.403)	(0.534)	(0.405)	(0.524)
N	3060	3060	3060	3060	3060	3060	3060	3060	3060	3060	3060	3060
Overall R2	0.9210		0.9210		0.9211		0.8129		0.7542		0.7195	
# Instruments		109		109		109		112		112		112
# Instruments / p		1,07		1,07		1,07		1,10		1,10		1,10
# Instruments / N		0,04		0,04		0,04		0,04		0,04		0,04
AR (1)		-5.77***		-5.61***		-5.78***		-5.90***		-6.50***		-6.08***
AR (2)		3.36***		3.20***		3.45***		2.10**		3.21***		2.82***
AR (3)		-2.33**		-2.35**		-2.68***		-0.82		-0.33		0.84
AR (4)		1.39		1.57		1.86*		/		/		/
Hansen Test J (p-value)		100.03		99.86		98.60		93.67		85.13		93.29
		(0.127)		(0.129)		(0.149)		(0.320)		(0.567)		(0.330)

Notes:

a) Robust standard errors are in parenthesis. *** p<0.01; ** p<0.05; * p<0.10.

b) In GMM-SYS estimates, the instrument set is curtailed according to the Arellano-Bond AR (#) Test. $e^{n}_{SSEpt-1}$ is instrumented with lags [t-4;t-5]. $e^{n}_{LSEpt-1}$ is instrumented with lags [t-3;t-4]. GMM models adopt two-step estimations and have been corrected with the Windmeijer (2005) covariance matrix for finite samples.

Appendix A2.5. Robustness Check #3: Different specification of supply concentration.

	SSE [1-2 listings]		SSE [1-3 listings]		SSE [1-4 listings]		LSE [3-10 listings]		LSE [4-10 listings]		LSE [5-10 listings]	
	RE	GMM-SYS	RE	GMM-SYS	RE	GMM-SYS	RE	GMM-SYS	RE	GMM-SYS	RE	GMM-SYS
ln Y (p, t-1)	0.4374***	0.1792***	0.4328***	0.1611**	0.4324***	0.1588***	0.2329***	0.2128**	0.2406***	0.3671***	0.2827***	0.4500***
	(0.047)	(0.061)	(0.047)	(0.065)	(0.046)	(0.058)	(0.030)	(0.085)	(0.033)	(0.080)	(0.035)	(0.098)
$ConcOverMedian_{pt-1}$	0.0605*	0.0819	0.0550*	0.0775	0.0550*	0.0786	-0.0645[81]	-0.0656	-0.1168***	-0.0818*	-0.1096**	-0.0565
	(0.032)	(0.053)	(0.032)	(0.049)	(0.032)	(0.051)	(0.039)	(0.045)	(0.044)	(0.045)	(0.051)	(0.053)
ln $MarketClimate^3_{pt}$	0.3321***	0.4873***	0.3366***	0.4990***	0.3364***	0.4988***	0.4913***	0.4952***	0.4602***	0.3620***	0.4023***	0.2904***
	(0.027)	(0.042)	(0.028)	(0.044)	(0.027)	(0.040)	(0.028)	(0.058)	(0.032)	(0.057)	(0.032)	(0.066)
ln $UnoccupiedDwellings_p$	0.1171***	0.1698***	0.1169***	0.1707***	0.1176***	0.1642***	-0.0295	-0.0272	-0.0562	-0.0566	-0.0557	-0.0308
	(0.027)	(0.044)	(0.026)	(0.045)	(0.026)	(0.043)	(0.037)	(0.042)	(0.047)	(0.050)	(0.046)	(0.050)
$UnemplRate_{pt}$	1.1624***	1.6368***	1.1497***	1.6897***	1.1628***	1.7223***	2.7517***	2.6617***	2.4212***	1.6931***	1.9747***	1.3134***
	(0.285)	(0.546)	(0.296)	(0.572)	(0.299)	(0.560)	(0.407)	(0.627)	(0.448)	(0.472)	(0.415)	(0.480)
$HighRangeSpecialized_p$	0.0400	0.0612	0.0383	0.0589	0.0363	0.0634	0.0790**	0.0865*	0.0892**	0.0866**	0.0739*	0.0623
	(0.025)	(0.044)	(0.024)	(0.044)	(0.025)	(0.045)	(0.039)	(0.050)	(0.042)	(0.040)	(0.044)	(0.046)
ln $AVGRent_{pt}$	-0.0110	-0.0231	-0.0103	-0.0218	-0.0097	-0.0197	-0.0400	-0.0495	-0.0026	-0.0156	0.0064	-0.0157
	(0.030)	(0.051)	(0.029)	(0.051)	(0.030)	(0.051)	(0.049)	(0.055)	(0.058)	(0.064)	(0.063)	(0.069)
ln $Altitude_p$	0.0467***	0.0670***	0.0463***	0.0687***	0.0442***	0.0671***	0.0199	0.0235	0.0192	0.0226	0.0005	0.0079
	(0.013)	(0.022)	(0.013)	(0.021)	(0.013)	(0.021)	(0.022)	(0.021)	(0.025)	(0.028)	(0.024)	(0.024)
$PercSeasideMunicipalities_p$	0.1423**	0.2189**	0.1437**	0.2298**	0.1422**	0.2280**	-0.0100	0.0121	-0.0309	-0.0044	-0.0783	-0.0297
	(0.060)	(0.092)	(0.059)	(0.104)	(0.059)	(0.100)	(0.084)	(0.112)	(0.104)	(0.099)	(0.099)	(0.091)
ln $BedHotels_p$	0.0588***	0.0879***	0.0581***	0.0892***	0.0582***	0.0927***	0.0598***	0.0655**	0.0529**	0.0608**	0.0426*	0.0334
	(0.016)	(0.025)	(0.016)	(0.028)	(0.016)	(0.027)	(0.021)	(0.028)	(0.024)	(0.027)	(0.023)	(0.024)
Constant	-3.3501***	-4.8635***	-3.3824***	-4.9642***	-3.3910***	-4.9340***	-3.6976***	-3.7964***	-3.3162***	-2.7061***	-2.7661***	-2.1780***
	(0.340)	(0.478)	(0.341)	(0.509)	(0.334)	(0.461)	(0.384)	(0.589)	(0.428)	(0.535)	(0.439)	(0.611)
N	3060	3060	3060	3060	3060	3060	3060	3060	3060	3060	3060	3060
Overall R2	0.9156		0.9152		0.9151		0.8042		0.7412		0.7064	
# Instruments		108		108		108		110		110		110
# Instruments / p		1,06		1,06		1,06		1,08		1,08		1,08
# Instruments / N		0,04		0,04		0,04		0,04		0,04		0,04
AR (1)		-5.24***		-4.98***		-5.27***		-5.55***		-6.46***		-6.03***
AR (2)		3.07***		2.84***		3.20***		2.37**		3.61***		3.07***
AR (3)		-2.84***		-2.92***		-3.24***		-1.25		-0.46		0.91
AR (4)		0.85		1.16		1.42		/		/		/
Hansen Test J (p-value)		100.26 (0.096)		99.83 (0.101)		99.65 (0.103)		93.74 (0.242)		86.13 (0.445)		92.86 (0.262)

Notes:

a) Robust standard errors are in parenthesis. *** p<0.01; ** p<0.05; * p<0.10.

b) In GMM-SYS estimates, the instrument set is curtailed according to the Arellano-Bond AR (#) Test. $e^n_{SSEpt-1}$ is instrumented with lags [t-4;t-5]. $e^n_{LSEpt-1}$ is instrumented with lags [t-3;t-4]. GMM models adopt two-step estimations and have been corrected with the Windmeijer (2005) covariance matrix for finite samples.

[81] The p-value is 0.102 (almost significant al 10% confidence level).

Appendix A2.6. Robustness Check #4: Different Estimation (Non-Dynamic Pooled OLS).

	SSE [1-2 list.]	SSE [1-3 list.]	SSE [1-4 list.]	LSE [3-10 list.]	LSE [4-10 list.]	LSE [5-10 list.]
$ConcentrationProp_{pt-1}$	0.0040	0.0030	0.0000	0.1179***	0.1819***	0.2104***
	(0.039)	(0.038)	(0.038)	(0.043)	(0.045)	(0.047)
$ConcentrationProp_{pt-1}$^2	0.0034	0.0033	0.0035	-0.0061**	-0.0097***	-0.0112***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
ln $Demand^3_{pt}$	0.6082***	0.6103***	0.6121***	0.5510***	0.4613***	0.3982***
	(0.022)	(0.022)	(0.022)	(0.032)	(0.035)	(0.038)
ln $UnoccupiedDwellings_p$	0.1912***	0.1905***	0.1897***	0.0103	0.0064	0.0150
	(0.040)	(0.040)	(0.040)	(0.047)	(0.055)	(0.056)
$UnemplRate_{pt}$	2.1370***	2.1102***	2.1450***	3.4921***	3.0074***	2.5245***
	(0.528)	(0.534)	(0.535)	(0.529)	(0.591)	(0.585)
$HighRangeSpecialized_p$	0.0523	0.0494	0.0457	0.1033**	0.1214**	0.1089*
	(0.045)	(0.044)	(0.044)	(0.050)	(0.052)	(0.057)
ln $AVGRent_{pt}$	-0.0468	-0.0444	-0.0434	-0.0849	-0.0530	-0.0437
	(0.053)	(0.052)	(0.052)	(0.058)	(0.061)	(0.070)
ln $Altitude_p$	0.0987***	0.0966***	0.0928***	0.0307	0.0312	0.0078
	(0.020)	(0.019)	(0.019)	(0.027)	(0.029)	(0.028)
$PercSeasideMunicipalities_p$	0.2917**	0.2884**	0.2886**	-0.2003	-0.3387**	-0.4425***
	(0.114)	(0.112)	(0.113)	(0.124)	(0.148)	(0.148)
ln $BedHotels_p$	0.0960***	0.0940***	0.0934***	0.0909***	0.0905***	0.0812***
	(0.025)	(0.025)	(0.024)	(0.027)	(0.027)	(0.028)
Constant	-5.7878***	-5.7855***	-5.7768***	-4.7455***	-4.3201***	-3.8406***
	(0.359)	(0.354)	(0.351)	(0.415)	(0.486)	(0.494)
N	3060	3060	3060	3060	3060	3060
R2	0.8997	0.8996	0.8996	0.7971	0.7346	0.6957

Appendix A2.7a. Descriptive Statistics for NUTS3 areas.

	AVG	STD-DEV	MEDIAN	MIN	MAX
Surface (sqkm)	2,821	1,717	2,470	213	7,692
Ray* (km)	28.6	8.9	28.0	8.2	49.5
Population (000)	563.7	616.1	387.9	84.4	4.335,8
# municipalities	73.9	54.1	60	6	312
% pop. of the main municipality	27.3%	15.0%	23.2%	7.8%	87.1%

* = ray if the provinces where represented by circles.

Appendix A2.7b. Robustness Check #5: sample excluding the NUTS3 of Rome, Florence and Naples.

	SSE [1-2 listings]		LSE [3-10 listings]	
	RE	GMM-SYS	RE	GMM-SYS
ln $Y_{p,t-1}$	0.4174***	0.1991***	0.2188***	0.2559***
	(0.044)	(0.061)	(0.026)	(0.080)
$ConcentrationProp_{p,t-1}$	0.0183	0.0155	0.0890**	0.1071**
	(0.027)	(0.048)	(0.039)	(0.043)
$ConcentrationProp^2_{p,t-1}$	0.0009	0.0018	-0.0046*	-0.0057**
	(0.002)	(0.003)	(0.002)	(0.003)
ln $MarketClimate^3_{p,t}$	0.3401***	0.4717***	0.4282***	0.3882***
	(0.031)	(0.047)	(0.032)	(0.058)
ln $UnoccupiedDwellings_p$	0.1243***	0.1653***	0.0082	0.0155
	(0.025)	(0.043)	(0.039)	(0.043)
$UnemplRate_{p,t}$	1.1994***	1.6458***	2.6946***	2.4190***
	(0.310)	(0.570)	(0.405)	(0.559)
$HighRangeSpecialized_p$	0.0357	0.0560	0.0803**	0.0767
	(0.027)	(0.043)	(0.040)	(0.047)
ln $AVGRent_{p,t}$	-0.0196	-0.0346	-0.0692	-0.0725
	(0.031)	(0.057)	(0.046)	(0.048)
ln $Altitude_p$	0.0561***	0.0754***	0.0240	0.0242
	(0.013)	(0.021)	(0.021)	(0.022)
$PercSeasideMunicipalities_p$	0.1357*	0.2286*	-0.1428	-0.1582
	(0.078)	(0.139)	(0.116)	(0.132)
ln $BedHotels_p$	0.0621***	0.0901***	0.0704***	0.0736***
	(0.016)	(0.025)	(0.021)	(0.026)
Constant	-3.4851***	-4.7649***	-3.7457***	-3.5802***
	(0.347)	(0.500)	(0.372)	(0.534)
Month fe	Yes	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes	Yes
N	3,000	3,000	3,000	3,000
Overall R2	0.9103		0.7874	
# Instruments		111		111
# Instruments / p		1,11		1,11
# Instruments / N		0,04		0,04
AR1 (p-value)		-5.25***		-5.90***
AR2 (p-value)		3.19***		2.78***
AR3 (p-value)		-2.80***		-1.13
AR4 (p-value)		0.93		/
Hansen Test J (p-value)		97.78 (0.162)		91.77 (0.342)

Notes:

a) Robust standard errors are in parenthesis. *** p<0.01; ** p<0.05; * p<0.10.

b) In GMM-SYS estimates, the instrument set is curtailed according to the Arellano-Bond AR (#) Test. $e^n_{SSEpt-1}$ is instrumented with lags [t-4;t-5]. $e^n_{LSEpt-1}$ is instrumented with lags [t-3;t-4]. GMM models adopt two-step estimations and have been corrected with the Windmeijer (2005) covariance matrix for finite samples.

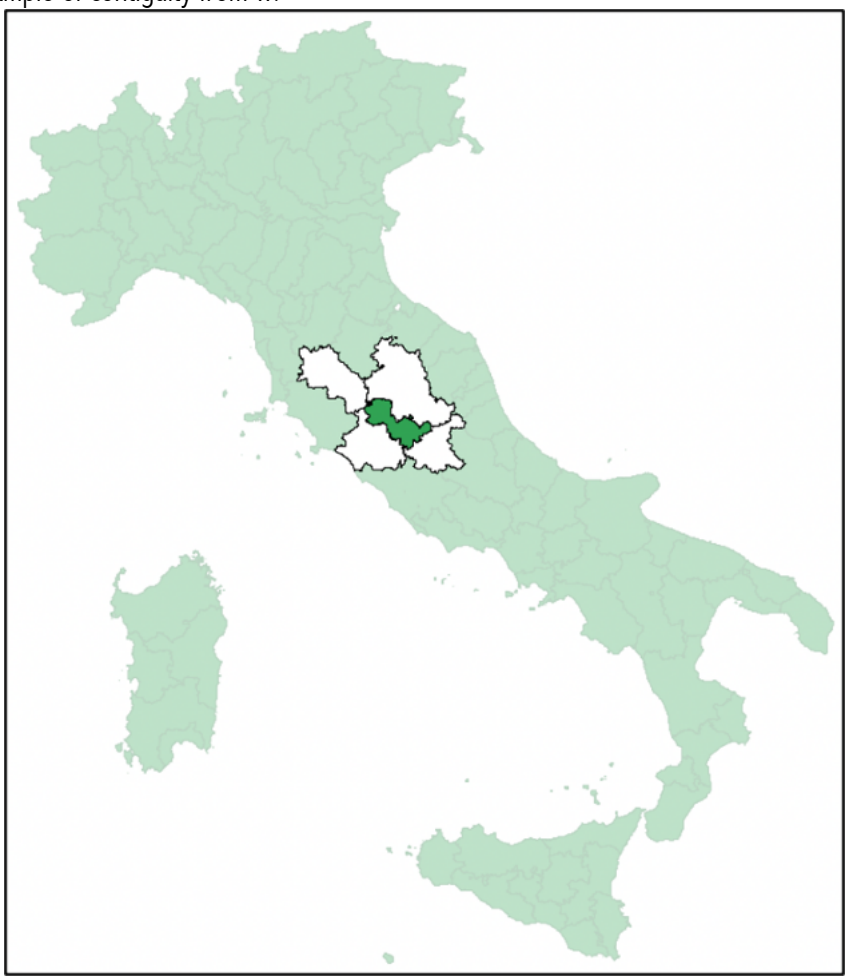
Appendix A2.7c. Robustness Check #6: econometric model with spatial lags.

	SSE [1-2]	LSE [3-10]
$ConcentrationProp_{p,t-1}$	0.067*	0.149***
	(0.030)	(0.033)
$ConcentrationProp^2_{p,t-1}$	-0.001	-0.008***
	(0.002)	(0.002)
ln $MarketClimate^3_{p,t}$	0.519***	0.488***
	(0.024)	(0.027)
W * $MarketClimate^3_{p,t}$	-0.000	0.002
	(0.002)	(0.002)
ln $UnoccupiedDwellings_p$	0.254***	0.052
	(0.048)	(0.048)
$UnemplRate_{p,t}$	1.134***	2.611***
	(0.431)	(0.491)
$HighRangeSpecialized_p$	0.102**	0.145***
	(0.027)	(0.045)
ln $AVGRent_{p,t}$	-0.046	-0.096*
	(0.057)	(0.056)
ln $Altitude_p$	0.103***	0.044*
	(0.024)	(0.023)
$PercSeasideMunicipalities_p$	0.353***	-0.049
	(0.133)	(0.133)
ln $BedHotels_p$	0.141***	0.144***
	(0.032)	(0.032)
Constant	-6.170***	-5.004***
	(0.404)	(0.392)
Month fe	Yes	Yes
Time Trend	Yes	Yes
N	3060	3060
Pseudo R2	0.897	0.797

Notes:

a) Spatial Panel Data Model employed.
b) W = Queen Contiguity Spatial Weight Matrix.
c) SSE = Small Scale Entrepreneurs managing 1 or 2 listings; LSE = Large Scale Entrepreneurs managing 3 to 10 listings.

Appendix A2.7d. Example of contiguity from W.



Notes:

a) The NUTS3 of Terni is displayed.
b) Queen contiguous neighbors are displayed.

Appendix A3 – Chapter 3

Appendix A3.1. First Stage Results with different pandemic beginnings.

	RC1 - Spec 1 s = 64 r = 250m	RC1 - Spec 1 s = 65 r = 250m	RC1 - Spec 1 s = 62 r = 250m	RC1 - Spec 2 s = 64 r = 500m	RC1 - Spec 2 s = 65 r = 500m	RC1 - Spec 2 s = 62 r = 500m	RC1 - Spec 3 s = 64 r = 750m	RC1 - Spec 3 s = 65 r = 750m	RC1 - Spec 3 s = 62 r = 750m	RC1 - Spec 4 s = 64 r = 1000m	RC1 - Spec 4 s = 65 r = 1000m	RC1 - Spec 4 s = 62 r = 1000m
ln COVID-19 Stringency Index(g,t)*POST*s*	-0.146***	-0.139***	-0.105***	-0.156***	-0.144***	-0.116***	-0.163***	-0.150***	-0.124***	-0.163***	-0.149***	-0.125***
	(0.004)	(0.004)	(0.003)	(0.005)	(0.005)	(0.003)	(0.005)	(0.005)	(0.003)	(0.005)	(0.005)	(0.003)
ln Average Market Price(i,r,t)	0.434***	0.434***	0.434***	0.615***	0.615***	0.614***	0.714***	0.714***	0.713***	0.790***	0.790***	0.790***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
ln RGDP(g,t)	1.981***	1.989***	1.992***	2.086***	2.096***	2.096***	2.011***	2.023***	2.020***	1.972***	1.983***	1.980***
	(0.017)	(0.017)	(0.017)	(0.018)	(0.018)	(0.018)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
ln CPI(g,t)	-0.812***	-0.777***	-0.702***	-0.869***	-0.816***	-0.765***	-0.764***	-0.703***	-0.665***	-0.753***	-0.690***	-0.662***
	(0.068)	(0.069)	(0.068)	(0.071)	(0.071)	(0.070)	(0.072)	(0.072)	(0.071)	(0.071)	(0.072)	(0.071)
ln Experience(i,t)	-0.012***	-0.012***	-0.012***	-0.015***	-0.015***	-0.015***	-0.016***	-0.016***	-0.016***	-0.016***	-0.016***	-0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-14.491***	-14.746***	-15.154***	-15.499***	-15.867***	-16.122***	-15.337***	-15.753***	-15.927***	-15.099***	-15.528***	-15.638***
	(0.288)	(0.288)	(0.283)	(0.296)	(0.297)	(0.291)	(0.296)	(0.296)	(0.290)	(0.295)	(0.295)	(0.288)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	2,205,347	2,205,347	2,205,347	2,205,347	2,205,347	2,205,347	2,205,347	2,205,347	2,205,347	2,205,347	2,205,347	2,205,347
Robust Standard Errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F	13,826.193	13,810.738	13,874.499	19,070.348	19,052.112	19,121.626	20,975.528	20,944.779	21,049.927	22,805.766	22,774.429	22,883.483
R^2	0.976	0.976	0.976	0.984	0.984	0.984	0.987	0.987	0.987	0.988	0.988	0.988
R^2 Adjusted	0.975	0.975	0.975	0.983	0.983	0.983	0.986	0.986	0.986	0.988	0.988	0.988
R^2 Within	0.054	0.054	0.054	0.076	0.076	0.076	0.087	0.087	0.087	0.097	0.096	0.097
R^2 Within Adjusted	0.054	0.054	0.054	0.076	0.076	0.076	0.087	0.087	0.087	0.097	0.096	0.097
AIC	-495,620.745	-495,138.061	-495,350.404	-317,254.354	-316,610.784	-317,121.671	-263,079.948	-262,351.065	-263,054.024	-239,690.378	-238,951.197	-239,759.774
BIC	-495,545.106	-495,062.423	-495,274.766	-317,178.716	-316,535.145	-317,046.033	-263,004.310	-262,275.426	-262,978.385	-239,614.739	-238,875.558	-239,684.135

Notes:

a) Subscripts: *i* = Property, *t* = Time (Year-Week), *g* = Country, 250/500/750/1000m = radius *r* defining the relevant market, *s* = definition of $POST_s$. Individual Fixed Effects stands for property-level (i) fixed effects included in the model.

b) Dependent variable = ln Local Airbnb Demand(i,r,t,f).

c) Estimates were generated by the means of Stata 17 (command *reghdfe*).

d) *** p<0.001, ** p<0.01, * p<0.5, + p<0.10.

Appendix A3.2. Second Stage Results with different pandemic beginnings.

	RC1 - Spec 1.1 s = 64 r = 250m	RC1 - Spec 1.2 s = 65 r = 250m	RC1 - Spec 1.3 s = 62 r = 250m	RC1 - Spec 2.1 s = 64 r = 500m	RC1 - Spec 2.2 s = 65 r = 500m	RC1 - Spec 2.3 s = 62 r = 500m	RC1 - Spec 3.1 s = 64 r = 750m	RC1 - Spec 3.2 s = 65 r = 750m	RC1 - Spec 3.3 s = 62 r = 750m	RC1 - Spec 4.1 s = 64 r = 1000m	RC1 - Spec 4.2 s = 65 r = 1000m	RC1 - Spec 4.3 s = 62 r = 1000m
ln Local Airbnb Demand(i,r,t)	0.090***	0.128***	0.073***	0.089***	0.129***	0.065***	0.086***	0.123***	0.065***	0.071***	0.105***	0.054***
	(0.018)	(0.019)	(0.019)	(0.017)	(0.018)	(0.017)	(0.016)	(0.017)	(0.016)	(0.016)	(0.017)	(0.015)
ln Average Market Price(i,r,t)	0.671***	0.655***	0.679***	0.743***	0.719***	0.758***	0.781***	0.755***	0.796***	0.814***	0.787***	0.827***
	(0.008)	(0.008)	(0.008)	(0.010)	(0.011)	(0.010)	(0.011)	(0.012)	(0.011)	(0.013)	(0.014)	(0.012)
ln RGDP(g,t)	0.387***	0.310***	0.420***	0.342***	0.258***	0.394***	0.320***	0.245***	0.364***	0.343***	0.272***	0.377***
	(0.037)	(0.039)	(0.038)	(0.036)	(0.039)	(0.036)	(0.033)	(0.036)	(0.033)	(0.033)	(0.036)	(0.032)
ln CPI(g,t)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
ln Experience(i,t)	0.002**	0.003**	0.002*	0.003***	0.004***	0.003***	0.004***	0.004***	0.003***	0.004***	0.005***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	2,205,346	2,205,346	2,205,346	2,205,346	2,205,346	2,205,346	2,205,346	2,205,346	2,205,346	2,205,346	2,205,346	2,205,346
Robust Standard Errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F	37,688.752	38,430.442	37,328.027	42,582.125	43,722.652	41,819.907	43,685.359	44,951.161	42,905.109	44,130.524	45,472.621	43,434.542
R^2 Adjusted	0.180	0.187	0.175	0.195	0.203	0.187	0.201	0.208	0.194	0.198	0.208	0.192
R^2 Uncentered	0.211	0.218	0.207	0.225	0.233	0.218	0.231	0.239	0.225	0.229	0.238	0.223
AIC	-2,023,566.852	-2,042,626.884	-2,011,415.303	-2,064,382.256	-2,085,980.456	-2,043,612.082	-2,080,564.492	-2,102,198.174	-2,062,099.418	-2,074,260.615	-2,100,446.529	-2,057,075.443
BIC	-2,023,516.426	-2,042,576.458	-2,011,364.878	-2,064,331.830	-2,085,930.030	-2,043,561.656	-2,080,514.066	-2,102,147.749	-2,062,048.992	-2,074,210.190	-2,100,396.104	-2,057,025.018
Kleibergen-Paap Underid. Test (rk LM)	1,082.248	933.598	1,193.196	1,113.966	900.740	1,323.847	1,229.208	971.401	1,545.349	1,229.900	961.274	1,611.162
Kleibergen-Paap Weak Id. Test (Wald F)	1,030.080	873.237	1,138.332	1,060.824	840.859	1,259.987	1,172.391	906.258	1,480.411	1,173.351	896.859	1,543.961
Cragg-Donald Weak Id. Test (Wald F)	2,476.075	2,034.140	2,279.317	2,623.212	2,036.993	2,554.966	2,864.371	2,194.635	2,887.851	2,833.554	2,154.186	2,943.777

Notes:

a) Subscripts: *i* = Property, *t* = Time (Year-Week), *g* = Country, 250/500/750/1000m = radius *r* defining the relevant market, *s* = definition of $POST_s$. Individual Fixed Effects stands for property-level (i) fixed effects included in the model.
b) Dependent variable = ln Average Weekly Price(i,t).
c) Estimates were generated by the means of Stata 17 (command *ivreghdfe*).
d) *** p<0.001, ** p<0.01, * p<0.5, + p<0.10.
e) The coefficient of ln CPI(g,t) is partialled out by the *ivreghdfe* estimation command because of collinearity with the fixed effects.

Appendix A3.3A. First Stage Results with different specifications of *f* in the definition of Local Airbnb Demand.

	RC2 - Spec 1.1 f = 2 r = 250m	RC2 - Spec 1.2 f = 4 r = 250m	RC2 - Spec 2.1 s = 62 r = 500m	RC2 - Spec 2.2 s = 64 r = 500m	RC2 - Spec 3.1 s = 65 r = 750m	RC2 - Spec 3.2 s = 62 r = 750m	RC2 - Spec 4.1 s = 64 r = 1000m	RC2 - Spec 4.2 s = 64 r = 1000m
ln COVID-19 Stringency Index(g,t,f)$POST_{63}$	-0.094***	-0.147***	-0.104***	-0.163***	-0.108***	-0.173***	-0.107***	-0.178***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
ln Average Market Price(i,r,t)	0.400***	0.473***	0.566***	0.672***	0.659***	0.783***	0.727***	0.868***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
ln RGDP(g,t)	2.035***	1.946***	2.146***	2.049***	2.070***	1.977***	2.025***	1.938***
	(0.018)	(0.017)	(0.019)	(0.018)	(0.020)	(0.018)	(0.020)	(0.018)
ln CPI(g,t)	-0.413***	-1.013***	-0.485***	-1.071***	-0.349***	-0.967***	-0.312***	-0.948***
	(0.070)	(0.066)	(0.073)	(0.068)	(0.074)	(0.068)	(0.074)	(0.068)
ln Experience(i,t)	-0.010***	-0.015***	-0.012***	-0.018***	-0.013***	-0.020***	-0.013***	-0.020***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-16.820***	-13.355***	-17.743***	-14.428***	-17.671***	-14.358***	-17.208***	-14.209***
	(0.295)	(0.275)	(0.303)	(0.282)	(0.302)	(0.281)	(0.302)	(0.279)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	1,877,764	2,649,779	1,877,764	2,649,779	1,877,764	2,649,779	1,877,764	2,649,779
Robust Standard Errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F	12,229.223	15,446.303	16,554.234	21,889.914	18,161.973	24,541.938	19,282.446	27,123.435
R^2	0.981	0.967	0.987	0.979	0.989	0.982	0.990	0.984
R^2 Adjusted	0.980	0.966	0.987	0.978	0.989	0.982	0.990	0.984
R^2 Within	0.058	0.049	0.079	0.072	0.090	0.084	0.096	0.094
R^2 Within Adjusted	0.058	0.049	0.079	0.072	0.089	0.084	0.096	0.094
AIC	-834,699.448	152,767.359	-664,442.995	328,615.322	-610,785.487	378,868.711	-549,815.145	398,162.182
BIC	-834,624.775	152,844.099	-664,368.322	328,692.062	-610,710.814	378,945.451	-549,740.471	398,238.921

Notes:

a) Subscripts: *i* = Property, *t* = Time (Year-Week), *g* = Country, 250/500/750/1000m = radius *r* defining the relevant market, *f* = definition of Demand Moving Average filter. Individual Fixed Effects stands for property-level (i) fixed effects included in the model.

b) Dependent variable = ln Local Airbnb Demand (i,r,t,f).

c) Estimates were generated by the means of Stata 17 (command *reghdfe*).

d) *** p<0.001, ** p<0.01, * p<0.5, + p<0.10.

Appendix A3.3B. Second Stage Results with different specifications of *f* in the definition of Local Airbnb Demand.

	RC2 - Spec 1.1 f = 2 r = 250m	RC2 - Spec 1.2 f = 4 r = 250m	RC2 - Spec 2.1 f = 2 r = 500m	RC2 - Spec 2.2 f = 4 r = 500m	RC2 - Spec 3.1 f = 2 r = 750m	RC2 - Spec 3.2 f = 4 r = 750m	RC2 - Spec 4.1 f = 2 r = 1000m	RC2 - Spec 4.2 f = 4 r = 1000m
ln Local Airbnb Demand(i,r,t,f)	0.027*	0.062*	0.027*	0.063**	0.030**	0.062**	0.023*	0.043+
	(0.013)	(0.026)	(0.012)	(0.023)	(0.011)	(0.022)	(0.011)	(0.022)
ln Average Market Price(i,r,t)	0.684***	0.696***	0.758***	0.779***	0.795***	0.822***	0.825***	0.860***
	(0.007)	(0.010)	(0.008)	(0.013)	(0.009)	(0.015)	(0.010)	(0.016)
ln RGDP(g,t)	0.440***	0.506***	0.405***	0.454***	0.373***	0.425***	0.375***	0.453***
	(0.027)	(0.054)	(0.026)	(0.051)	(0.024)	(0.048)	(0.023)	(0.048)
ln CPI(g,t)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
ln Experience(i,t)	0.001	0.001	0.002**	0.002**	0.003***	0.003**	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	2,649,779	1,877,764	2,649,779	1,877,764	2,649,779	1,877,764	2,649,779	1,877,764
Robust Standard Errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F	42,699.919	31,286.331	47,843.176	35,577.604	49,190.863	36,594.511	50,065.905	36,816.781
R^2 Adjusted	0.185	0.207	0.197	0.222	0.205	0.228	0.204	0.223
R^2 Uncentered	0.185	0.207	0.197	0.222	0.205	0.228	0.204	0.223
AIC	-2,246,477.121	-1,772,142.787	-2,286,494.820	-1,807,912.947	-2,310,336.991	-1,821,719.064	-2,306,917.582	-1,811,055.374
BIC	-2,246,425.961	-1,772,093.004	-2,286,443.660	-1,807,863.164	-2,310,285.831	-1,821,669.281	-2,306,866.422	-1,811,005.592
Kleibergen-Paap Underid. Test (rk LM)	1,739.146	658.856	1,989.568	728.352	2,276.719	825.248	2,445.904	805.491
Kleibergen-Paap Weak Id. Test (Wald F)	1,701.859	635.848	1,956.491	705.460	2,262.170	804.105	2,440.587	783.313
Cragg-Donald Weak Id. Test (Wald F)	3,589.873	1,610.170	4,184.810	1,781.372	4,687.678	1,924.656	4,957.665	1,828.674

Notes:

a) Subscripts: *i* = Property, *t* = Time (Year-Week), *g* = Country, 250/500/750/1000m = radius *r* defining the relevant market, *f* = definition of Demand Moving Average filter. Individual Fixed Effects stands for property-level (i) fixed effects included in the model.

b) Dependent variable = ln Average Weekly Price(i,t).

c) Estimates were generated by the means of Stata 17 (command *ivreghdfe*).

d) *** p<0.001, ** p<0.01, * p<0.5, + p<0.10.

e) The coefficient of ln CPI(g,t) is partialled out by the *ivreghdfe* estimation command because of collinearity with the fixed effects.

Appendix A3.4A. Second Stage Results for different specifications of Private Hosts.

Note: Private Host = Hosts with Properties Managed <= Thresh (2 or 4).

	RC3 - Spec 1.1 Thresh = 2 r = 250m	RC3 - Spec 1.2 Thresh = 4 r = 250m	RC3 - Spec 2.1 Thresh = 2 r = 500m	RC3 - Spec 2.2 Thresh = 4 r = 500m	RC3 - Spec 3.1 Thresh = 2 r = 750m	RC3 - Spec 3.2 Thresh = 4 r = 750m	RC3 - Spec 4.1 Thresh = 2 r = 1000m	RC3 - Spec 4.2 Thresh = 4 r = 1000m
ln Local Airbnb Demand(i,r,t)	-0.031	0.007	-0.004	0.014	0.001	0.025	-0.006	0.016
	(0.024)	(0.019)	(0.022)	(0.017)	(0.019)	(0.015)	(0.019)	(0.015)
ln Average Market Price(i,r,t)	0.538***	0.623***	0.625***	0.703***	0.673***	0.741***	0.711***	0.775***
	(0.011)	(0.008)	(0.014)	(0.011)	(0.014)	(0.011)	(0.015)	(0.012)
ln RGDP(g,t)	0.573***	0.519***	0.498***	0.467***	0.470***	0.418***	0.472***	0.426***
	(0.048)	(0.038)	(0.046)	(0.036)	(0.039)	(0.032)	(0.038)	(0.032)
ln CPI(g,t)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
ln Experience(i,t)	-0.000	0.001	0.001	0.002*	0.001	0.003**	0.002*	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	1,261,031	1,808,542	1,261,031	1,808,542	1,261,031	1,808,542	1,261,031	1,808,542
Robust Standard Errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F	10,034.925	22,578.192	12,802.559	25,820.622	14,727.340	27,209.265	15,655.602	27,923.251
R^2 Adjusted	0.031	0.108	0.076	0.131	0.095	0.147	0.097	0.147
R^2 Uncentered	0.069	0.142	0.113	0.164	0.130	0.180	0.133	0.180
AIC	-1,142,853.959	-1,670,830.920	-1,203,735.425	-1,717,292.795	-1,228,720.507	-1,751,825.760	-1,232,502.815	-1,751,749.739
BIC	-1,142,805.770	-1,670,781.288	-1,203,687.236	-1,717,243.163	-1,228,672.317	-1,751,776.128	-1,232,454.626	-1,751,700.107
Kleibergen-Paap Underid. Test (rk LM)	686.197	1,097.861	681.761	1,159.755	862.927	1,371.912	913.461	1,413.494
Kleibergen-Paap Weak Id. Test (Wald F)	656.764	1,052.660	655.983	1,116.655	835.400	1,330.608	885.159	1,372.799
Cragg-Donald Weak Id. Test (Wald F)	1,413.171	2,274.133	1,479.929	2,496.147	1,834.507	2,890.220	1,904.464	2,933.571

Notes:

a) Subscripts: *i* = Property, *t* = Time (Year-Week), *g* = Country, 250/500/750/1000m = radius *r* defining the relevant market Individual Fixed Effects stands for property-level (i) fixed effects included in the model.

b) Dependent variable = ln Average Weekly Price(i,t).

c) Estimates were generated by the means of Stata 17 (command *ivreghdfe*).

d) *** p<0.001, ** p<0.01, * p<0.5, + p<0.10.

e) The coefficient of ln CPI(g,t) is partialled out by the *ivreghdfe* estimation command because of collinearity with the fixed effects.

Appendix A3.4b. Second Stage Results for different specifications of Commercial Hosts.

Note: Commercial Host = Hosts with Properties Managed > Thresh (2 or 4).

	RC3 - Spec 1.1 Thresh = 2 r = 250m	RC3 - Spec 1.2 Thresh = 4 r = 250m	RC3 - Spec 2.1 Thresh = 2 r = 500m	RC3 - Spec 2.2 Thresh = 4 r = 500m	RC3 - Spec 3.1 Thresh = 2 r = 750m	RC3 - Spec 3.2 Thresh = 4 r = 750m	RC3 - Spec 4.1 Thresh = 2 r = 1000m	RC3 - Spec 4.2 Thresh = 4 r = 1000m
ln Local Airbnb Demand(i,r,t)	0.145***	0.349***	0.099***	0.315***	0.113***	0.280***	0.096***	0.249***
	(0.029)	(0.051)	(0.026)	(0.049)	(0.027)	(0.053)	(0.028)	(0.053)
ln Average Market Price(i,r,t)	0.812***	0.817***	0.912***	0.896***	0.938***	0.937***	0.971***	0.966***
	(0.013)	(0.022)	(0.017)	(0.031)	(0.020)	(0.038)	(0.022)	(0.042)
ln RGDP(g,t)	0.293***	0.002	0.313***	-0.022	0.230***	0.002	0.257***	0.061
	(0.059)	(0.103)	(0.057)	(0.111)	(0.058)	(0.117)	(0.057)	(0.114)
ln CPI(g,t)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
ln Experience(i,t)	0.003*	0.009***	0.004**	0.010***	0.004***	0.008***	0.005***	0.009***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	944,309	396,797	944,309	396,797	944,309	396,797	944,309	396,797
Robust Standard Errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F	30,014.178	16,382.880	32,520.186	20,305.928	29,439.205	20,030.789	28,479.344	19,215.309
R^2 Adjusted	0.281	0.253	0.275	0.265	0.272	0.273	0.265	0.275
R^2 Uncentered	0.308	0.282	0.302	0.293	0.299	0.301	0.293	0.303
AIC	-840,358.624	-281,400.557	-832,446.024	-287,747.858	-828,429.072	-292,052.485	-820,200.003	-293,237.300
BIC	-840,311.591	-281,356.992	-832,398.991	-287,704.294	-828,382.040	-292,008.920	-820,152.971	-293,193.735
Kleibergen-Paap Underid. Test (rk LM)	471.481	209.441	569.236	227.332	559.714	200.610	549.437	199.732
Kleibergen-Paap Weak Id. Test (Wald F)	461.228	211.465	559.112	230.561	554.069	203.463	546.037	203.862
Cragg-Donald Weak Id. Test (Wald F)	1,098.872	559.117	1,318.773	596.540	1,272.156	522.170	1,236.142	511.888

Notes:

a) Subscripts: *i* = Property, *t* = Time (Year-Week), *g* = Country, 250/500/750/1000m = radius *r* defining the relevant market Individual Fixed Effects stands for property-level (i) fixed effects included in the model.

b) Dependent variable = ln Average Weekly Price(i,t).

c) Estimates were generated by the means of Stata 17 (command *ivreghdfe*).

d) *** p<0.001, ** p<0.01, * p<0.5, + p<0.10.

e) The coefficient of ln CPI(g,t) is partialled out by the *ivreghdfe* estimation command because of collinearity with the fixed effects.

Appendix A4 – Chapter 4

Appendix A4.1. Industrial Sectors analyzed.

Panel A. Share of selected industrial sectors over the total industry.

		Share "Closer" Industrial Sectors			
		AVG	STD. DEV	MIN	MAX
Control Group	n.a.	78,58%	8,45%	44,63%	100,00%
Treat Group	Pre - Treat	77,84%	6,94%	57,07%	100,00%
	Post - Treat	78,06%	6,90%	0,00%*	100,00%
TOTAL	n.a.	78,15%	7,35%	0,00%*	100,00%

Notes:

a) Share "Closer" Industrial Sectors = Number of firms active in "Closer" industrial sectors divided by the total number of firm active in a Borgo *i* at time *t*.

b) "Closer" Industrial Sectors = Primary (e.g., agriculture or fishing), Secondary (manufacturing), Trade, Transportation, Hospitality, Financial services, Real Estate, Travel Agencies and services supporting firms, and Entertainment.

c) The minimum of 0% happened in one case only, when in the Borgo of Scarperia in 2015. The second value after this minimum is 45%.

Panel B. Sub-industrial sectors.

INDUSTRIAL SECTOR	CODE	ATECO	SUB-SECTORS
Primary Sector	PR	A	Agriculture, forestry, and fishing.
Secondary Sector	MFCG	C	Manufacturing activities for: food, beverage, tobacco, textile, clothing, leather, wood, paper, multiple chemical products, metallurgy, various electronics products, transportation, and furniture.
Trade	TRD	G	Wholesale and retail trade for automotive product, wholesale trade for other products (no automotive), retail trade for other products (no automotive).
Transportation	TRSP	H	Terrestrial transportation, sea transportation, airline transportation, activities in support to transportation services, postal services.
Hospitality	HSP	I	Restaurants and general hospitality services.
Financial Services	FIN	K	General financial services (no insurance), Insurance services, and supporting activities to financial services.
Real Estate	RE	L	Real estate services.
Travel Agencies and Support Services	TA-NOL	N	Rental or leasing operators, travel agencies, vigilance services, general support activities.
Entertainment	ENT	R	Artistic activities, libraries and museums, and sports or other general entertainment activities.

Notes:

a) INDUSTRIAL SECTOR refers to the explanation in Section 4.2. where the various dependent variables have been introduced.

b) CODE = code used in the tables of the paper (note: this code has been decided by the authors).

c) ATECO = corresponding first-level ATECO Code (see https://codiceateco.it).

Appendix A4.2. Effects of Airbnb by market sectors, without controlling for $FIRMS_{i,t-1}$.

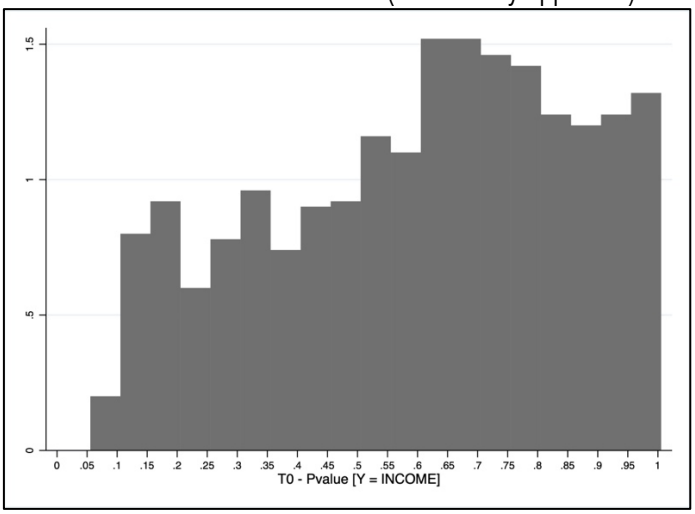
	PR	MFCG	TRD	TRSP	HSP	FIN	RE	TA-NOL	ENT
T-2 back	-0.006	-0.041*	0.018	-0.025	-0.012	0.042+	-0.021	-0.023	-0.002
	(0.021)	(0.020)	(0.019)	(0.021)	(0.016)	(0.023)	(0.021)	(0.025)	(0.024)
	(0.790)	(0.046)	(0.350)	(0.217)	(0.474)	(0.072)	(0.324)	(0.346)	(0.938)
T0	0.006	0.005	-0.010	0.013	0.014	-0.002	0.036	0.049+	0.006
	(0.022)	(0.022)	(0.020)	(0.022)	(0.017)	(0.025)	(0.023)	(0.026)	(0.026)
	(0.783)	(0.819)	(0.631)	(0.549)	(0.435)	(0.951)	(0.113)	(0.063)	(0.816)
T+1	0.006	0.005	-0.020	0.047*	0.030	0.003	0.041+	0.033	0.052+
	(0.024)	(0.023)	(0.022)	(0.023)	(0.018)	(0.026)	(0.024)	(0.028)	(0.028)
	(0.807)	(0.825)	(0.345)	(0.043)	(0.107)	(0.900)	(0.082)	(0.238)	(0.059)
T+2	0.032	0.020	-0.012	0.075**	0.052**	0.009	0.048+	0.028	0.085**
	(0.025)	(0.024)	(0.023)	(0.024)	(0.019)	(0.028)	(0.025)	(0.029)	(0.029)
	(0.202)	(0.417)	(0.591)	(0.002)	(0.007)	(0.735)	(0.056)	(0.333)	(0.003)
T+3	0.048+	0.057*	0.002	0.109***	0.071***	0.006	0.098***	0.035	0.127***
	(0.026)	(0.025)	(0.024)	(0.026)	(0.020)	(0.029)	(0.026)	(0.031)	(0.030)
	(0.065)	(0.023)	(0.928)	(0.000)	(0.001)	(0.849)	(0.000)	(0.255)	(0.000)
T+4 on	0.045+	0.070**	-0.009	0.124***	0.094***	0.013	0.094***	0.067*	0.121***
	(0.025)	(0.024)	(0.023)	(0.025)	(0.019)	(0.028)	(0.025)	(0.029)	(0.029)
	(0.071)	(0.004)	(0.710)	(0.000)	(0.000)	(0.653)	(0.000)	(0.023)	(0.000)
Constant	49.834***	31.356***	43.303***	28.093***	34.321***	13.262***	22.323***	19.301***	5.739*
	(2.132)	(2.059)	(1.946)	(2.081)	(1.649)	(2.363)	(2.142)	(2.490)	(2.474)
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.020)
$X_{i,t}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
η and τ	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,853	2,853	2,853	2,853	2,853	2,853	2,853	2,853	2,853
Overall R2	0.010	0.001	0.000	0.000	0.001	0.002	0.008	0.000	0.003
Between R2	0.008	0.001	0.000	0.000	0.001	0.003	0.010	0.000	0.001
Within R2	0.264	0.208	0.223	0.209	0.258	0.129	0.147	0.273	0.134

Notes:

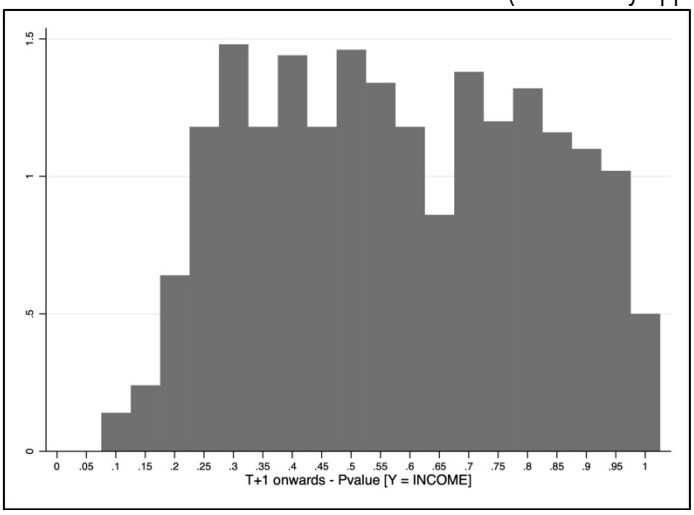
a) *** p<0.001; ** p<0.01; * p<0.05; + p<0.10. Bootstrapped standard errors and p-value in parentheses.
b) Dependent variables are log-transformed.
c) PR = Primary Sector (e.g., agriculture or fishing); MFCG = Secondary Sector (Manufacturing); TRD = Trade; TRSP = Transportation; HSP = Hospitality (e.g., restaurants & traditional hospitality); FIN = Financial Services; RE = Real Estate; TA-NOL = Travel Agencies & Support services; ENT = Entertainment.
d) Leads and Lags must be interpreted compared to T-1 (one year before the treatment assignment).
e) T-2 back = from 2 years before treatment to the first available lag; T+4 on = from 4 years after treatment to the last available obs.
f) The model does not control for $FIRMS_{i,t-}$.

Appendix A4.3. P-values distribution from Placebo #1 ($Y_{i,t}$ = $INCOME_{i,t}$)

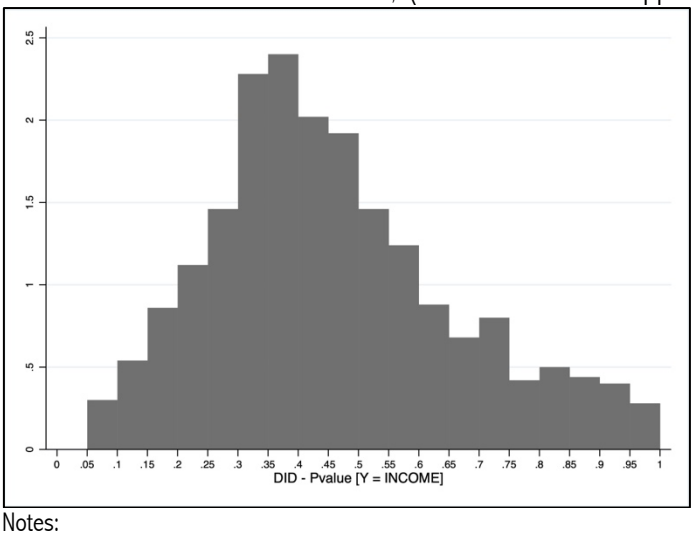
Panel A. P-values distribution of T0 (event study approach).



Panel B. P-values distribution of T+1 onwards (event study approach).



Panel C. P-values distribution of $DID_{i,t}$ (standard TWFE DID approach).



Notes:

a) Based on 1,000 random allocations of treatment, to treated units, in the pre-treatment phase.
b) See section 4.5.3.1a. for further information.

Appendix A4.4. First Stage Results.

	$Y_{i,t} = DID_{i,t}$
IV	0.019***
	(0.004)
	(0.000)
Constant	2.827
	(7.318)
	(0.699)
Control Variables $X_{i,t}$	Yes
TimeFE τ	Yes
N	2,451
Pseudo R2	0.372
Area Under ROC Curve (AUC)	0.880

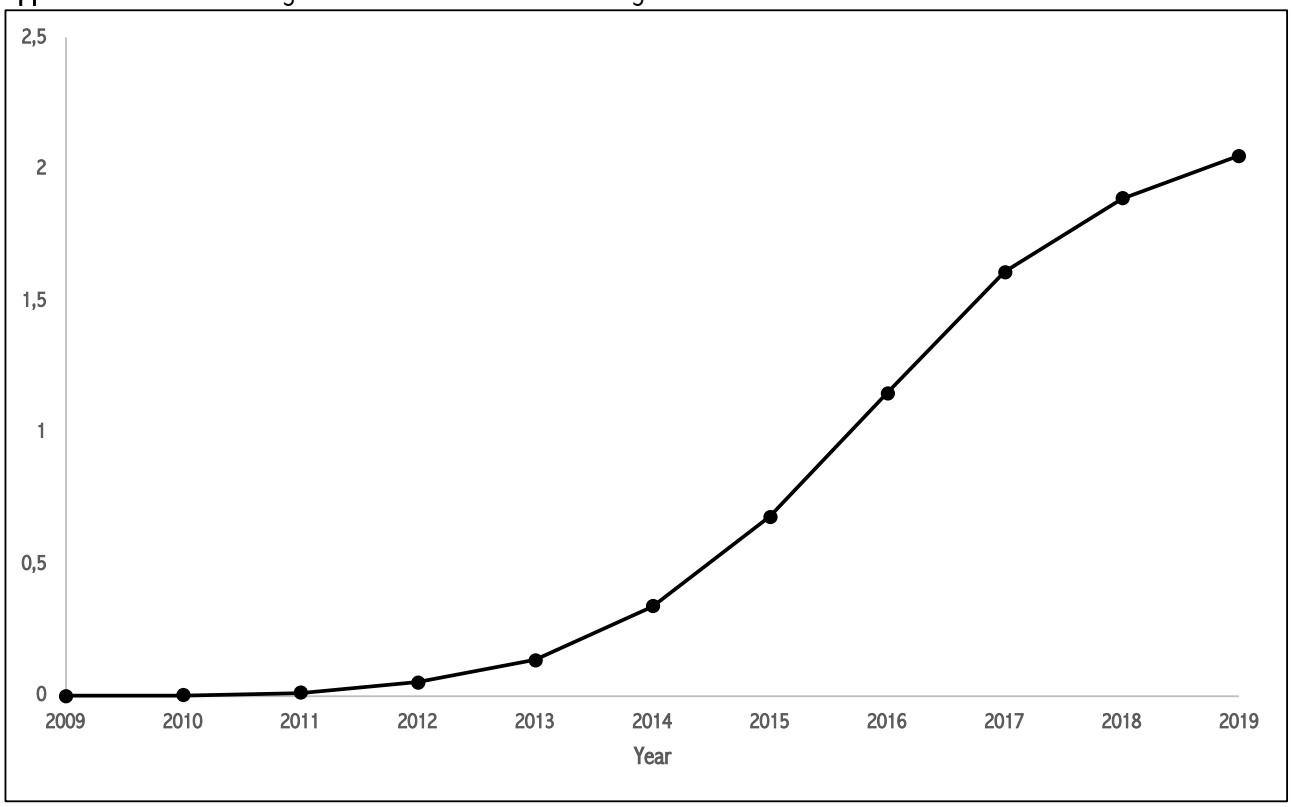
Appendix A4.5. CEM Approach – Standard TWFE DID Approach.

	$INCOME_{i,t}$	$INCOMEpc_{i,t}$	$FIRMS_{i,t}$
$DID_{i,t}$	0.063*	0.020	0.016*
	(0.032)	(0.016)	(0.008)
	(0.049)	(0.190)	(0.035)
Constant	63.946+	9.675	10.813+
	(34.537)	(35.590)	(5.850)
	(0.065)	(0.786)	(0.066)
Control Variables $X_{i,t}$	Yes	Yes	Yes
IndividualFE η and TimeFE τ	Yes	Yes	Yes
N	2595.000	2589.000	2580.000
Overall R2	0.005	0.197	0.002
Between R2	0.006	0.210	0.002
Within R2	0.126	0.271	0.171

Notes:

a) *** p<0.001; ** p<0.01; * p<0.05; + p<0.10. Robust standard errors and p-value in parentheses.
b) Dependent variables are log-transformed.
c) Sample is based on CEM (see Section 5.3.3.)

Appendix A4.6. Airbnb stage of diffusion within treated Borghi.



Notes:

a) On the Y axis there is the mean value of Airbnb Penetration (i.e., Active Airbnb per squared kilometer) of all treated Borghi in a given year.
b) The year is shown on the X axis.