Amenities, urban consumption and tourism

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Abstract

In this paper, we investigate how tourism shapes local consumption amenities in cities. To do so, we combine a novel geo-located dataset of monthly retail establishments (licenses) with the number of tourist accommodations (Airbnb rooms) and develop an empirical strategy based on IV panel techniques to address endogeneity concerns. Average results show that tourism positively affects the number of establishment licenses. However, this effect is mainly related to tourist-oriented retail activities (e.g., bars and restaurants), while more resident-oriented establishments are negatively affected. This latter result highlights the segregating and re-shaping effect of tourism on retail activity in city centers.

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1 Introduction

In the last years, economists have studied the city as a center of consumption. Since Glaeser et al. (2001), researchers shifted their attention to the importance of local consumption amenities and the recent discussion has focused on the spatial distribution of consumption and on the role of amenities in predicting gentrification. While the prevailing perspective characterises consumers as residents, there exists a gap in considering the impact of tourists. Tourism involves the temporary relocation of consumers across space and acts as a powerful catalyst for significant local economic dynamism. The existing literature not only establishes tourism as a significant source of income and employment but also carefully identifies its geographical determinants. However, by linking the concept of city as a centre of consumption to the influence of tourism, a further contribution is given to the recent debate around the cities' touristification and consumption segregation.

This paper explores the causal impact of tourism on shaping the distribution of local consumption activities within cities. Specifically, we examine whether the introduction of new tourism accommodations influences the density of licenses required for offering goods and services (bars and restaurants) locally. This is motivated by the fact that beyond the direct effects of tourism on the local markets, these considerations are relevant for understanding the impacts of touristification on households' welfare. Moreover, we focus on retailers, bars, and restaurants since they constitute a significant portion of household expenditures, regardless of income level.

Our findings indicate that shifts in tourism activities positively stimulate the release of consumption licenses. Furthermore, the heterogeneous analysis uncovers distinct behaviours across different categories of consumption amenities and delineates tourism-oriented and non-tourism-oriented categories. In summary, these results demonstrate that tourism affects city amenities in diverse ways, providing additional insights into the broader urban spatial structure and, in turn, offering new perspectives on urban gentrification and consumption segregation.

Our analysis focuses on the period between 2015 and 2019 and investigates the city of Turin, which serves as an exemplary case for several reasons. Firstly, owing to recent municipal administrations, the city has been augmenting its tourism significance and appeal by leveraging its cultural heritage, proximity to mountains and hills (i.e., the Alps and Langhe), and hosting international events (such as the Winter Olympic Games in

2006 and the ATP Finals from 2021 to 2025). In 2019, Turin ranked as the sixth most visited city in Italy among major cities??, experiencing a 49.6% increase in tourist arrivals and a 66.5% surge in the number of nights from 2009 to 2018??. Secondly, the absence of regulations and the consistent supply of traditional accommodations (e.g., hotels and bed & breakfasts) in Turin allow us to implement our empirical strategy by focusing solely on Airbnb's active listings as a reliable proxy for tourist accommodations in the city.

To study the effect of tourism on local consumption amenities we combine a set of data concerning the period between 2015 to 2019. We have access to a high-quality novel dataset about the consumption licenses released in Turin. It reports the active licenses and specifies their location and category. Moreover, we take advantage of Airbnb's daily listings. We aggregate the data and obtain a large monthly panel data at the census tract spatial level. The baseline identification strategy relies on estimating the relationship between the monthly number of consumption licenses active in a census tract and the tourist accommodations' density. In all regression analyses, we incorporate controls for time, spatial, and category fixed-effects. The fine granularity of the data enables us to consider the distinct characteristics within each category, thereby enhancing the accuracy of estimations compared to a more generalized aggregate measure. Additionally, we adapt this strategy to assess the heterogeneous effects across license categories. In such instances, our sample is restricted to the specific category analyzed, with the inclusion of time and census tract fixed effects.

To establish a robust causal relationship in both contexts, we deal with a critical identification concern: local time-variant unobservable characteristics, such as the ongoing gentrification process, may influence our specification. This is in addition to the potential simultaneous determination of tourist accommodations and economic activities, particularly in the most attractive areas of the city. To mitigate this issue, we control for a set of variables addressing socio-demographic characteristics, rent fluctuations, and changes in agglomeration economies over time in the area, and propose an instrumental variable to introduce exogenous variation for tourist accommodations.

The instrumental variable approach employs a Bartik-like instrument, created through the interaction between the share of empty apartments per census tract in 2011 and the Google search interest in Airbnb from 2015 to 2019. The share component and the Google Trend predict the locations and timings of the listings, respectively. To support the exclusion, we show that our share component predates our period by four years and does not predict the number of consumption licenses, even when considering the dynamic effect.

This paper contributes to multiple strands of literature. We engage with existing literature on urban consumption amenities, which predominantly focuses on two aspects, both look at resident consumption. One part explores gentrification processes in American cities. For instance, Couture and Handbury (2020) highlight how divergent amenity valuations across age and education groups drive urban revival in downtown neighborhoods. Additionally, Baum-Snow and Hartley (2020) analyze the relevance of local amenities preferences across several racial groups, while Behrens et al. (2023) identifies pioneer industries, particularly cultural and creative sectors, fostering gentrification in its early stages.

On the other hand, the literature examines the geography of urban consumption. Initial contributions point out the role of transit time in consumer choice (Couture, 2016; Miyauchi et al., 2021). However, Davis et al. (2019) contends that ethnic and racial frictions play a more significant role than spatial ones. Moreover, residents' consumption choices are directly related to the number of services provided (Couture, 2016).

Our paper also contributes to the relatively limited literature regarding tourism's consequences on economic development. Early studies primarily focus on how tourism specialization propels economic growth (?Sequeira and Maçãs Nunes, 2008; Arezki et al., 2009). Despite variations in geographical determinants (McGregor and Wills, 2017), these studies generally show that tourism has a positive and significant impact on GDP.

Recently, literature has shed light on various economic spillovers of tourism, emphasizing the substantial and significant local economic gains it generates. For instance, Faber and Gaubert (2019) explores tourism spillovers on the manufacturing industry in Mexico, Nocito et al. (2023) focuses on increased income and expenditures in municipalities in Sicily, and Favero and Malisan (2021) demonstrates increased income, firms, and employment in industrial sectors in Matera (2019 European Capital of Culture).

Furthermore, the paper aligns with recent literature on home-sharing platforms, particularly the effects of the Airbnb platform. This literature explores various perspectives, including the housing market (Sheppard et al., 2016; Horn and Merante, 2017; Garcia-López et al., 2020; Barron et al., 2021; Koster et al., 2021; Franco and Santos, 2021), traditional accommodations (Zervas et al., 2017; Farronato and Fradkin, 2022), residents' welfare (Almagro and Domınguez-Iino, 2022; Calder-Wang, 2021), and neighborhood investments (Xu and Xu, 2021).

Our contribution is specifically related to literature investigating the effects on the local economy (Alyakoob and Rahman, 2018; Basuroy et al., 2020; Hidalgo et al., 2022). Conceptually, Basuroy et al. (2020) and Hidalgo et al. (2022) are the most similar to our study. Basuroy et al. (2020) uses ZIP level Airbnb reviews and restaurant revenues data in Texas, employing a Difference in Difference strategy to show a 0.011% increase in restaurant revenues associated with a 1% increase in Airbnb reviews. In contrast, Hidalgo et al. (2022) evaluates the impact of Airbnb listings on food and beverage establishments and employment in Madrid census tracts. Their instrumental variable results indicate a 0.0355 increase in the average number of establishments and a 0.8972 increase in employment for each additional Airbnb room.

We contribute to these strands of literature as follows. First, we provide new evidence regarding the effects of tourist activities on economic development, particularly on consumption amenities within cities, such as retailers, bars and restaurants. To the best of our knowledge, this is the first paper examining the role of tourists as an additional source of consumption, demonstrating that tourism positively influences the average supply of consumption amenities. Second, we investigate heterogeneous effects across retailers, bars, and restaurant licenses in Turin. Unlike Basuroy et al. (2020) and Hidalgo et al. (2022), who leverage multiple industries for falsification tests, we disentangle our overall findings and show that the effect may be distinguished between tourist-oriented activities (e.g., bars and restaurants) rather than resident-oriented establishments. Third, we propose a new Bartik instrument to address endogenous issues related to the non-randomized distribution of tourist accommodations. Lastly, we analyze a European city, which is relevant since most literature examines local consumption amenities in US cities. Despite marked differences between US and European cities, this allows for comparisons with previous studies.

The paper is structured as follows: Section **??** introduces our main data sources and describes the most relevant variables. In Section 3, we elaborate on our identification strategy. The main results are provided and discussed in Section 4. Section 5 discusses the robustness of the results, and Section 6 concludes.

2 Background

In this section, we describe the databases we leverage. Due to the distinct spatial levels of aggregation in the data, we opt to use the census tract level as our spatial unit for two reasons. The census tract represents the smallest level of aggregation in Italy, ensuring homogeneity in socio-economic characteristics within its defined area. Second, the considerable number of census tracts, 3850 in total, along with the variations in local economic and demographic features among these tracts, provides a robust foundation for meaningful measurements.

2.1 Consumption licenses

We employ a dataset provided by Turin's City Council to acquire information on active consumption amenities licenses spanning from January 2012 to December 2019. This dataset encompasses a variety of establishments, including retailers, bars, and restaurants, categorized into 41 distinct groups (refer to Table A.??). Notably, service providers are excluded from our analysis. The license information incorporates details such as the license category, the coordinates of the establishments, as well as the opening and closure dates.

When launching a new shop or restaurant, the owner is required to request a license. Importantly, this request incurs no additional cost for the applicant. A single establishment or applicant may be associated with more than one license, with the number of licenses contingent on the goods offered. For instance, if a newsagent intends to sell coffee in the shop, two separate licenses are required. In our analysis, we prioritize the use of the opening and closure dates of licenses as a more reliable measure of the local economy's evolution than relying solely on the establishment's stock and turnover. This approach enables us to not only capture the establishment's opening and closure but also provide a more accurate representation of the locally provided goods. Utilizing the opening and closure date information, we construct a variable that tracks the number of active licenses each month, categorized by type.

2.2 Touristic accommodations

The second database presents a daily record of active and available Airbnb listings in Turin spanning from January 2015 to December 2019. This comprehensive listing is sourced from AirDna, which directly extracts data from the Airbnb website. Each day's listing encompasses details for every property available for booking or already booked, including specific information for each dwelling or room, such as exact coordinates, the number of rooms, and the maximum guest capacity. Notably, the listing is not limited to individual dwelling owners, it also includes various traditional hosts, such as hotels or bed and breakfast establishments, leveraging the Airbnb platform to showcase and offer their accommodations. Given the diverse composition of hosts, we can just focus on no-traditional accommodations as a proxy for tourist activities out of the traditional ones. Specifically, our focus is on the number of rooms, serving as a representative measure of the overall phenomenon.

Each property is linked to its corresponding census tract, and the daily listing data is aggregated at the monthly level. Consequently, the monthly count of rooms reflects whether a property, multiplied by its number of rooms, has been available or booked for at least one day during the month.

A third dataset provides details on traditional accommodations in the city, specifically hotels and Bed and breakfasts, on an annual basis. This dataset enriches our understanding of the overall tourist accommodation supply in the city, complementing the information derived from Airbnb listings.

2.3 Controls

We enrich our dataset by integrating information from two supplementary sources. First, we obtained rental data from the Osservatorio Immobiliare Italiano (OMI), with a specific focus on commercial rent data. This enhancement enables us to account for fluctuations in prices across both temporal and spatial dimensions.

Second, we compiled various socio-demographic variables from the statistical department of the City Council of Turin. This collection encompasses key metrics, including population density, age composition, the proportion of foreign residents, and various variables derived from the 2011 National Census.

Table 1: Summary statistics of Airbnb and licences variables

Year	Variable	Mean	St. Dev.	Min	Max
	N. of Airbnb	0.461	1.105	0	18
2015	N. of Airbnb Rooms	0.567	1.408	0	21
	N. of Licenses	7.249	8.607	0	94
	N. of Airbnb	0.556	1.220	0	17
2016	N. of Airbnb Rooms	0.641	1.462	0	22
	N. of Licenses	7.345	8.752	0	96
	N. of Airbnb	0.589	1.221	0	20
2017	N. of Airbnb Rooms	0.703	1.513	0	25
	N. of Licenses	7.408	8.826	0	108
	N. of Airbnb	0.558	1.190	0	19
2018	N. of Airbnb Rooms	0.653	1.468	0	27
	N. of Licenses	7.472	8.918	0	112
	N. of Airbnb	0.564	1.178	0	16
2019	N. of Airbnb Rooms	0.671	1.502	0	26
	N. of Licenses	7.422	8.850	0	100

Notes: the Table reports the descriptive statistics by year of the number of Airbnb properties active and available on the platform, the number of Airbnb rooms active and available on the platform, and the number of retailers and bar/restaurants licenses active in the city.

Table 2: Summary statistics for six selected license categories

Category	Year 2015	Year 2016	Year 2017	Year 2018	Year 2019
Appliances and Electr.	0.2 (0.557)	0.201 (0.557)	0.203 (0.562)	0.203 (0.559)	0.2 (0.554)
Articles Gift	0.01 (0.098)	0.009 (0.096)	0.011 (0.104)	0.011 (0.106)	0.012 (0.11)
Bar and Restaurants	1.496 (1.959)	1.518 (2.035)	1.521 (2.02)	1.552 (2.066)	1.567 (2.082)
Flower and plants	0.054 (0.262)	0.056 (0.269)	0.055 (0.27)	0.055 (0.272)	0.054 (0.265)
Newspapers	0.115 (0.381)	0.113 (0.376)	0.109 (0.368)	0.106 (0.364)	0.105 (0.363)
Supermarket	0.169 (0.468)	0.175 (0.477)	0.188 (0.501)	0.198 (0.531)	0.212 (0.556)

Notes: the Table reports for a sample of categories the mean and the standard deviation, in parenthesis, of the number of licences active in the city each year.

2.4 Descriptive Statistics

Table 1 presents the descriptive statistics for key variables each year, including the count of listed Airbnb properties, the active supply of Airbnb rooms, and the overall number of consumption licenses. Analyzing the evolution of touristic accommodations, we observe a general increase in the mean over time, despite a slight decrease in 2018. Notably, the standard deviations are more than double in magnitude compared to their respective means. These substantial standard deviation values indicate significant cross-census tract variations in listings each year. Figure 1 further visualizes the distribution of Airbnb rooms in Turin in January 2015 and January 2019, suggesting not only the cross-census tract variations suggested by the standard deviation but also an increasing variability across the years.

To complete the overview of touristic accommodations, Table A2 outlines the supply of traditional accommodations per year. Notably, there is a marginal increase of only 14 units between 2015 and 2019, indicating stability in the stock throughout the years.

Examining consumption licenses, we observe a modest increase over the years and notable cross-census tract variation, as illustrated in Figure 2, mirroring the trends in tourism variables. Additionally, Table 2 provides detailed mean and standard deviation values for six selected license categories (those examined in the heterogeneous analysis).

Figure 1: Rooms distribution on January 2015 (left) and on January 2019 (right)

Notes: Figure show the distribution of the rooms active and available in Turin on January 2015 (on the left) and on January 2019 (on the right)

While these categories may exhibit diverse behaviors influenced by tourism activities, all of them show a consistent mean from 2015 to 2019.

3 Empirical Strategy

3.1 Baseline Specification

This paper aims to capture the causal relationship between tourism and local economic activities. The absence of regulations and the consistent supply of traditional accommodations in the city allow us to implement our empirical strategy by focusing solely on Airbnb's active listings as a reliable proxy for tourist accommodations in the city. To address this question, our main analysis follows a panel fixed-effects regression:

$$Ln(NLicenses_{itj}) = \beta NRooms_{it} + \gamma X_{it} + \mu_i + \tau_t + \delta_j + \epsilon_{ijt} \tag{1}$$

The dependent variable is the logarithm of the licenses' number of category j in a census tract i at time t. Our explanatory variable, $NRooms_{it}$, is the number of accommodations' rooms in a census tract i a time t. Specifically, we just focus on the Airbnb rooms, since the traditional accommodation supply is steady from 2015 to 2019. The specification includes the census tract fixed-effects, μ_i, that account for time-invariant

Figure 2: Licences distribution on January 2015 (left) and on January 2019 (right)

Notes: Figure show the distribution of licences in Turin on January 2015 (on the left) and on January 2019 (on the right)

characteristics of census tracts, the time fixed-effects, τ_t, and the category fixed-effects, δ_j.

Our baseline setting exploits a set of control variables (X_{it}) to deal with several gentrification processes that might directly affect the distribution of the license. First, we use several socio-demographic time-variant variables at the census tract level to address the changes in the population characteristics over our period of interest and to control for the diverging people preferences that might directly impact the amenities distribution (Couture and Handbury, 2020): the population density, the share of a foreign resident, the average size of families, the share of young people (<30 years) and the share of older people (>65 years). Second, we introduce the commercial rent prices at the census tract level. The rent cost represents the main cost for a license's owner, for this reason, it might increase the barriers to entry in the market in the most expensive part of the city. Third, we construct two variables to measure the merchandise category specialization and diversity at the census tract level. These controls allow us to consider the agglomeration externalities within and among categories if they exist.

3.2 Instrumental Variable

Our baseline specification might be biased due to endogeneity issues. Our independent variable is likely correlated with unobservable time-varying specifics and census tract characteristics, grouped in the error term. Besides, the reverse causality matters, considering that several license categories might have positive or negative effects on Airbnb availability. To deal with these endogeneity problems, we develop an instrumental variable approach.

Our strategy is based on a Bartik-like instrument, therefore, the instrument is built as the interaction of a "shift" component with a "share" one. The shift factor reflects the evolution over time of touristic activities, while the share one describes the touristic activities' variations across census tracts. Therefore $Shift\text{-}Share_{it}$ is construct as:

$$Shift\text{-}Share_{it} = GoogleTrend_t \ * \ Share2011_i \tag{2}$$

Focusing on the 'share' component, the share of empty apartments per census tract in 2011, namely $Share2011_i$, incorporates why an area offers a different stock of Airbnb listings compared to another one. We argue that an area with a higher share of empty apartments is more likely to experience a higher stock of Airbnb accommodations over time. Indeed, the switch from an empty apartment to a short-term rental accommodation represents a remunerative alternative for the apartment's owner. This intuition is strictly related to recent evidence regarding the home-sharing market, according to which Airbnb leads a reduction in long-term rental supply to capitalize on the short-term rental price premium (Horn and Merante, 2017; Garcia-López et al., 2020; Barron et al., 2021).

On the other hand, we use the worldwide Google trends, $GoogleTrend_t$, of the word "Airbnb" to construct the 'shift' components. This specification takes advantage of the methodology proposed by Garcia-López et al. (2020), Barron et al. (2021), Hidalgo et al. (2022), who use this variable to predict when the listing appears. The variable is directly provided by Google and reports the monthly trend where the lowest value is normalized to zero, and the highest to 100. As the authors point out, Google Trend is a reliable proxy of the general level of interest towards the platform, both supply and demand sides.

We check for the power of the shift-share interaction in the first stage and we now proceed to discuss the exclusion restriction. Since we are using a shift-share instrument, we need to deal with both components. Regarding the shift component, the Google Trend should be correlated with the number of licenses to break the restriction, but it seems unlikely since we are working with the worldwide Google trend, then it is independent of our specific case study (Barron et al., 2021). Additionally, Goldsmith-Pinkham et al. (2020) confirm that the primary validity concerns may arise from the share component. In this case, the share of empty apartments in 2011 should be correlated to our dependent variable just through the Airbnb listings. This circumstance seems plausible because we are exploiting a time-invariant variable dating back to four years before the period we are investigating. Moreover, before 2011, only 19 Airbnb accounts existed in Turin, insufficient to argue that Airbnb increased the share of empty apartments. As additional support for the validity, Figure A4 shows the dynamic effect of the outcome variable, the logarithm of license numbers in the tracts, on the 2011 share of empty apartments, as suggested by Goldsmith-Pinkham et al. (2020). This analysis assesses if tracts with more empty apartments before 2015 exhibited different trends, which could explain our baseline results. However, this seems unlikely, since the pre-2015 effects are not statistically significant. Additionally, we examine the potential predictive power of empty apartment shares on Airbnb room occurrence. Table A3 presents two longitudinal regression results with the 2011 share of empty apartments as the explanatory variable, one including time-fixed effects and the other without. In both cases, the coefficient indicates the effectiveness of empty apartment shares in predicting the number of Airbnb rooms.

3.3 Heterogeneous Effects

The second part of our analysis aims to disentangle the overall effect obtained by Eq. (1) to point out the heterogeneous effect across the license categories. With this purpose, Eq. (1) becomes:

$$NLicenses_{it} = \beta NRooms_{it} + \gamma X_{it} + \mu_i + \tau_t + \epsilon_{it} \tag{3}$$

The variables are exactly the ones presented previously. In Eq. (3), we do not insert licenses fixed-effect since we run the OLS over a sub-sample composed of the specific category analyzed. Eq. (3) suffers from the same endogeneity issues as Eq. (1), then we exploit the instrumental variable approach previously displayed (Eq. 2).

Table 3: Baseline results

	(1) OLS	(2) IV	(3) IV
N° Rooms	0.0001	0.0046***	0.0080***
	(0.0001)	(0.0017)	(0.0029)
Rent Control	Yes	No	Yes
Sociodem. Control	Yes	No	Yes
Spec/Div Control	Yes	No	Yes
Month FE	Yes	Yes	Yes
Census FE	Yes	Yes	Yes
Category FE	Yes	Yes	Yes
Obs.	9471000	9471000	9471000

Table 4: First stage baseline results

	(1) IV First St.	(2) IV First St.
Shift-Share	0.0305***	0.0301***
	(0.0038)	(0.0038)
Rent Control	No	Yes
Sociodem. Control	No	Yes
Spec/Div Control	No	Yes
Time FE	Yes	Yes
Census FE	Yes	Yes
Category FE	Yes	Yes
Obs.	9471000	9471000
KP F-statistic	65.895	64.278

Notes: in Table 3 the dependent variable is the logarithm of the number of licenses. In Table 4 the dependent variable is the number of Airbnb rooms. Significance is indicated by * p<0.1. ** p<0.05, and *** p<0.001. Standard errors, in parenthesis, are clustered at census tract levels. The analysis takes place at the census tract-month level. Controls are grouped into i) Rent Control which accounts for the average commercial rent, ii) Sociodem. Control includes the population density, the share of foreign residents, the share of the population with age between 0 and 29 years, the share of the population with more than 66 years old, and the average number of families. iii) Spec/Div Control includes the Specialization and Diversity variables.

4 Results

4.1 Baseline and IV results

Table 3 illustrates the results of our baseline specification and the instrumental variable approach. The analysis focuses on the logarithm of the number of consumption licenses, regressed on the availability of touristic accommodations. Specifically, the explanatory variable is the number of rooms listed on Airbnb, encompassing both independent units and rooms offered by traditional hosts. This variable, $NRooms$, reflects the scale of tourism activity in the city.

Column 1 of the table details the baseline specification (Eq. 1), incorporating fixed effects for the time, census tract, and category, and controls for rent, socio-demographic factors, and agglomeration economies. These controls account for different area responses to gentrification. In this column, the coefficient is negative and not significant, which aligns with expectations due to the endogeneity bias intrinsic in Eq. 1. We also explore this specification with varying combinations of contemporaneous controls and fixed effects, but the results remain consistent.

Columns 2 and 3 present the outcomes of the instrumental variable approach in its second stage. The specification corresponds to Eq. 2, where tourism activities are instrumented using the interaction between the 2011 cross-area share of vacant apartments and Google Trend searches. Column 2 excludes controls, while Column 3 includes them, maintaining fixed effects for time, census tract, and category. In both configurations, the coefficients are positive and statistically significant, indicating that an increase in touristic accommodations leads to a rise in local consumption amenities, especially when leveraging an exogenous instrument. Notably, the magnitude of the coefficients in these columns varies slightly with the inclusion of controls. Specifically, the inclusion of socio-demographic characteristics, average commercial rent, and area specialization and diversity (as in column 3) leads to a slight increase in the coefficient. Additionally, Table A5 examines various control combinations in the instrumental variable specifications, revealing only minor variations in our estimates. This consistency suggests that our instrument is not likely correlated with unobserved census tract characteristics.

For a practical interpretation, we focus on the most stringent specification. Our findings suggest that an average increase of one Airbnb listing in a census tract corresponds to an average 0.8% increase in the total number of amenities licenses. Considering the average number of licences in 2017 is 7.422, an increase of 100 Airbnb rooms would lead to an increase of 5.9 licences in the area.

To test the relevance of the instrument, we present the first-stage results in Table 4, along with the respective F-statistics, which exceed the commonly accepted threshold of 10 (Angrist and Pischke, 2008). Moreover, to further support the instrument's strength, Table A4 displays the reduced-form results, where the instrumental variable significantly and positively influences the logarithm of license numbers in the area.

Overall, the various specifications consistently suggest that a greater supply of touristic activities enhances local consumption amenities. contributes by shedding light on a broader and more general impact of tourism on urban amenities than the related literature.

4.2 Heterogeneous Effects Results

In this subsection, we proceed to present the analysis of the heterogeneous effects among the consumption amenities licenses. Building on previous findings (Section 4.1) that indicate a significant positive impact of tourism activities on local consumption amenities, our focus is now on disentangling the overall effect by examining each licence

Table 5: Licenses categories - *Notes*: Categories are divided between Tourism (left) No-Tourism oriented (right)

No-Tourism Oriented			Tourism Oriented		
Category	Sign	Significance	Category	Sign	Significance
Animals Articles	+		Automatic Machines	+	***
Appliances and Electronics	+		Bar and Restaurants	+	***
Building Material	+	***	Candies	+	***
Children Articles	−		Clothing	−	***
Cosmetics and Perfumery	−		Coffee Pods	+	***
Extralimentary	−	***	Food	+	***
Fabrics and Rugs	−	***	Gift Articles	+	***
Flowers and Plants	+		Hairdressers and Beauticians	+	***
Fuels	−	***	Mixed	+	***
Furniture	+		Objects	+	***
Games	−		Second Hand	−	***
Hardware Store	+		Sport Articles	+	*
Health and Orthopedic Articles	+	*	Supermarkets	+	***
Home Articles	−	***			
House and Person Hygiene Articles	+				
Jewellery	−				
Laundry	−				
Libraries	−				
Motor and Car	−				
Musical Instruments	+	*			
Newspapers	−	***			
Optics	+	*			
Pharmacy and Herbalist Articles	−	***			
Photography	−	***			
Sexy Shop	+	**			
Spare Accessories	−				
Stationery Articles	−	*			
Tobacco	+				

Notes: the Table resume the heterogenous results. The sign column reports the coefficients sign and significance is indicated by * p<0.1. ** p<0.05, and *** p<0.001. Standard errors are clustered at census tract levels. The analysis takes place at the census tract-month level. Results are conditioned on controls which include i) Rent Control which accounts for the average commercial rent, ii) Sociodem. Control includes the population density, the share of foreign residents, the share of the population with age between 0 and 29 years, the share of the population with more than 66 years old, and the average number of families. iii) Spec/Div Control includes the Specialization and Diversity variables.

category individually.

Table 5 summarizes the results for each category using the instrumental variable approach. The specifics for these categories are detailed in Tables 6, 7, and in the Appendix (Tables A7 to A12). Our estimates allow for identifying both tourism-oriented and no-tourism-oriented categories. Indeed, in Table 5, the categories are already divided in between this distinction. To the best of our knowledge, the literature does not offer a precise allocation of each category to tourism-oriented and no-tourism-oriented.

The primary heterogeneous results are discussed, concentrating on six representative categories, i.e. three tourism-oriented and three non-tourism-oriented. Moreover, we choose to aggregate the categories in either tourism or non-tourism distinction to investigate how the overall effect of touristic accommodations changes based on their classification.

In Table 6, we report on tourism-oriented categories including Bars and Restaurants, Supermarkets, and Gift Articles. Conversely, Table 7 focuses on non-tourism cat-

Table 6: Impact of tourism on tourism-oriented categories

	(1) IV Tourism	(2) IV Bar/Rest	(3) IV Supermarket	(4) IV Art.Gift
N° Rooms	0.0341***	0.0972***	0.1043***	0.0133***
	(0.0064)	(0.0220)	(0.0194)	(0.0035)
Rent Control	Yes	Yes	Yes	Yes
Sociodem. Control	Yes	Yes	Yes	Yes
Spec/Div Control	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Census FE	Yes	Yes	Yes	Yes
Obs.	3003000	231000	231000	231000

Notes: the dependent variable is the logarithm of the number of licenses. Significance is indicated by * p<0.1. ** p<0.05, and *** p<0.001. Standard errors, in parenthesis, are clustered at census tract levels. The analysis takes place at the census tract-month level. Controls are grouped into i) Rent Control which accounts for the average commercial rent, ii) Sociodem. Control includes the population density, the share of foreign residents, the share of the population with age between 0 and 29 years, the share of the population more than 66 years old, and the average number of families. iii) Spec/Div Control includes the Specialization and Diversity variables.

egories such as Appliances and Electronics, Newspapers, and Flowers and Plants. We present these results using the most demanding specification of the instrumental variable approach, which includes time and census tract fixed effects, in addition to rent, socio-demographic characteristics, and agglomeration economies controls.

The tourism-oriented aggregation (column 1 of Table 6) exhibits a positive and highly significant effect. Similarly, Bars and Restaurants, Supermarkets, and Gift Articles (columns 2-4 respectively) show significant positive coefficients. Notably, Bars and Restaurants demonstrate a positive effect, as in the study by Hidalgo et al. (2022). This discrepancy in results is attributed to different empirical strategies and the specific city under study. However, an increase in tourist accommodations boosts each tourism-related category, though not uniformly. For instance, Supermarkets experience a significantly larger effect compared to Gift Articles.

The category of Clothing, as detailed in Table A12, requires additional attention due to its negative and significant coefficient. To explain this result, we investigate the possibility of small clothing shops being replaced by larger establishments, such as malls This substitution effect would result in a significant decrease in clothing licenses. To verify this hypothesis, we exploit our instrumental variable approach (Eq. 2) with the logarithm of the number of clothing establishments with a surface lower than 250 squared meters[1]

[1] We follow the definition of small establish provided by the City's Council

Table 7: Impact of tourism on no-tourism-oriented categories

	(1) IV No-Tourism	(2) IV Appl/Elect	(3) IV Newspapers	(4) IV Flowers/Plants
N° Rooms	-0.0046***	0.0032	-0.0131***	0.0032
	(0.0015)	(0.0076)	(0.0037)	(0.0022)
Rent Control	Yes	Yes	Yes	Yes
Sociodem. Control	Yes	Yes	Yes	Yes
Spec/Div Control	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Census FE	Yes	Yes	Yes	Yes
Obs.	6468000	231000	231000	231000

Notes: the dependent variable is the logarithm of the number of licenses. Significance is indicated by * p<0.1. ** p<0.05, and *** p<0.001. Standard errors, in parenthesis, are clustered at census tract levels. The analysis takes place at the census tract-month level. Controls are grouped into i) Rent Control which accounts for the average commercial rent, ii) Sociodem. Control includes the population density, the share of foreign residents, the share of the population with age between 0 and 29 years, the share of the population with more than 66 years old, and the average number of families. iii) Spec/Div Control includes the Specialization and Diversity variables.

as the explanatory variable. The negative estimate with a high significance (Table A13) supports our substitution hypothesis.

Regarding non-tourism-oriented categories (column 1 of Table 7), the overall estimate is negative and significant. However, individual category results vary. For instance, an increase in tourism accommodations correlates with a significant decrease in Newspaper licenses (column 3), while having no significant effect on Appliances/Electronics and Flowers/Plants (columns 2 and 4 respectively).

These findings prompt a clear distinction between tourism-oriented and non-tourism-oriented categories. As expected, tourism activities enhance tourism-related licenses. Following the literature, we point out a positive and significant effect of food and beverages licenses and, in addition, we investigate the other tourism-oriented categories. In contrast, non-tourism-related licenses exhibit a mixed response, ranging from reductions to non-significant changes, emphasizing that the positive impact of tourism is predominantly associated with tourism-oriented activities.

5 Robustness Checks

We now present a list of alternative exercises to test the robustness of our results to changes in the specification and control variables. These exercises involve: i) using a different tourism measure, ii) modifying the time and spatial units, iii) assessing the impact of specification changes incorporating trends, iv) examining potential lagged effects on the outcome variable, and v) addressing potential spillover effects.

5.1 Tourism Measure

In Table A6, we exhibit robust results using an alternate metric for tourist activities. This metric is the logarithm of the number of Airbnb properties within a census tract, specifically counting properties listed on the Airbnb platform for at least one day in a month. This measure aims to assess the impact of each new accommodation, regardless of its size.

Column 1 presents the OLS setting, which shows an insignificant and negative coefficient, attributed to endogeneity issues. However, the instrumental variable approach, detailed from column 2 to column 9, rectifies this issue. In these columns, we present outcomes with varied control variable sets. Similar to the main findings in Table **??**, these results consistently show positive and significant effects for the predictor variable across all specifications. Besides, the magnitude of the coefficient increases in the most demanding specification (0.0261 in column 9) compared to the baseline estimates (0.0080 in column 3 of Table 3).

5.2 Spatial and Time Unit

We have primarily focused our analysis at the census tract level, examining monthly variations. This subsection introduces modifications to our identification strategy by exploring alternative spatial and temporal units separately.

Initially, we replicate our instrumental variable approach, utilizing both the OMI and neighbourhood administrative separations[2]. Figure A2 and A3 illustrate the boundaries of the 63 OMI areas and the 23 neighborhoods, respectively. The results of the instrumental variable specification for both OMI and neighborhood-level analysis are presented in Table A14. At the OMI level, we observe a positive and significant effect without controls (column 1) and a similar outcome when covariates are included. However, at the neighborhood aggregation, the effect turns negative and statistically insignificant (columns 3

[2]The administrative boundaries are provided by Turin City's Council

and 4), suggesting that the impact of tourism is not substantial at larger spatial scales like neighborhoods.

Additionally, we extend our analysis considering the variations in tourism accommodations and activity licenses over quarters and semesters at the census tract level. The results of this analysis are summarized in Table A15. Consistent with our primary findings, this approach also reveals a positive and highly significant effect on the instrumental variable specification, reinforcing the robustness of our results across different time frames.

5.3 Trends

We now incorporate time trends into the baseline specification. Initially, we assess potential time trends across census tract and licence categories. Given that certain categories tend to be more prevalent in specific city areas, this specification accounts for changes in these trends. We adopted the detrending method previously applied by Garcia-López et al. (2020). The results, shown in Column 1 of Table A16, indicate a positive, but not highly significant, effect.

We propose a second exercise, in which we introduce interaction terms between the time trend and the 2015 control variables as additional regressors. Additionally, we factor in the interaction between the time trend and the proximity to the city center. This adjustment allows for potentially steeper time trends in more central neighborhoods. Column 2 of Table 1 displays these findings, revealing a coefficient smaller and less significant than in the baseline specification, but still positive.

5.4 Lagged Variable

In this section, we evaluated whether the impact of tourism on local economic activities is delayed. Recognizing that the effect of tourism might not manifest immediately on local economies, we have developed a specification that incorporates a lagged explanatory variable. Since we work at the month level, we consider lagged months. Specifically, Table A17 displays the results, where column 1 considers the number of Airbnb rooms at time $t-1$, column 2 at time $t-2$, and column 3 at time $t-3$.

The results across these columns consistently show positive effects and all are statistically significant. Additionally, the magnitude of the effect diminishes when considering variables with a greater lag.

5.5 Spillover

An important concern in our empirical analysis is the risk of spillover effects. These effects arise from the proximity of the census tracts under study, where activities in one tract could potentially affect adjacent tracts. To address this, we propose a strategy of omitting areas adjacent to the administrative boundaries of neighbourhoods from our initial sample. While there may be differences within a single neighbourhood, the disparities between different neighbourhoods tend to be more pronounced. The use of individual fixed effects helps to mitigate the impact of externalities from surrounding areas, especially those that have had a steady influence over the study period. Nevertheless, such influences tend to be more pronounced between neighbourhoods. By also removing the bordering areas of adjacent neighbourhoods, as shown in Figure A5, we make further progress in isolating neighbourhood-specific differences and reducing the potential for cross-neighbourhood spillovers.

Table A18 presents the results obtained from the sample reduced to the green areas depicted in Figure A5. Although there is an increase in the effect's magnitude relative to the baseline results, it remains positive and highly significant, both with and without the inclusion of controls.

6 Conclusions

Tourism is a source of consumption. In the recent discussion regarding the gentrification processes and geography of consumption, tourism is inevitably involved.

This paper delves into the impact of tourism activities on the distribution of local consumption amenities, with a particular focus on the city of Turin between 2015 and 2019. Our approach combines detailed data on active consumption licenses and Airbnb listings in an empirical strategy that includes panel fixed-effect regression, a range of control variables, and an innovative instrumental variable approach. Indeed, the empirical strategy relies on a Bartik-like instrument, which combines the share of empty apartments per census tract in 2011 with the Google Trend data for the keyword "Airbnb". This approach has allowed us to address the endogeneity issues typically associated with the distribution of touristic accommodations.

The results show that tourism activities foster positively the overall release of the consumption licenses. This result underscores the role of tourism in stimulating local economies, particularly in the context of urban centers. Furthermore, our analysis reveals insights regarding the behavior of local consumption amenities. We identify distinct impacts across various categories of consumption amenities, pointing out a distinction between tourism-oriented and no-tourism-oriented categories. Tourism-oriented categories generally show positive and significant effects, while non-tourism-oriented categories display either negative significant effects or no significant impact.

In terms of internal validity, the methodological framework, including the robustness checks, lends credibility to our findings. The use of local data on licenses and Airbnb listings provides a granular view of the impact of tourism within cities, further strengthening the reliability of our conclusions. However, when considering external validity, it is important to note that the study focuses on Turin, and the findings might not be directly generalizable to other contexts with different urban dynamics and tourism patterns. Nevertheless, the findings provide a valuable framework for understanding the interplay between tourism and urban consumption amenities in other cities.

Overall, this research contributes by introducing a new methodological approach and offering new perspectives on the influence of tourism in city centers. The evidence presented sheds light on the segregating and reshaping effects of tourism on city amenities. Furthermore, the findings have practical implications for public policy, particularly in the management of touristification, a relevant topic in many cities across the United States and Europe.

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Appendix

We follow Garcia-López and Muñiz (2013) to define $Spec_{itj}$ and Div_{itj}.

- $Spec_{itj}$ is the specialization of category j in census tract i in the month t:

$$Spec_{itj} = \frac{NLicenses_{itj}/NLicenses_{it}}{NLicenses_{tj}/NLicenses_{t}}$$

- Div_{itj} is the diversity of category j in census tract i in the month t:

$$Div_{itj} = \frac{1/\sum_{j'=1 j'\neq j}^{J} (\frac{NLicenses_{itj'}}{NLicenses_{it}-NLicenses_{itj}})^2}{1/\sum_{j'=1 j'\neq j}^{J} (\frac{NLicenses_{tj'}}{NLicenses_{t}-NLicenses_{tj}})^2}$$

Tables

Table A.A1: Licences' Category list

Bar and Restaurants	Health and Orthopedic Articles
Supermarkets	Automatic Machines
Gift Articles	Home Articles
Appliances and Electronics	Animals Articles
Newspapers	Photography
Flowers and Plants	Tobacco
Objects	Musical Instruments
Jewellery	Extralimentary
Fabrics and Rugs	Furniture
Coffee Pods	Pharmacy and Herbalist Articles
Candies	Spare Accessories
Hardware Store	Games
Sexy Shop	Fuels
Second Hand	Hairdressers and Beauticians
Optics	Building Material
Stationery Articles	Clothing
Cosmetics and Perfumery	Children Articles
Motor and Car	Libraries
Sport Articles	House and Person Hygiene Articles
Mixed	Laundry
Food	

Notes: the Table includes the list of licence categories in the dataset.

Table A.A2: Traditional Accommodation Details

	2015	2016	2017	2018	2019
Hotel	134	132	132	131	131
Hotel Residence	12	11	10	11	11
Hostel	9	11	12	12	15
Residence	49	55	56	60	67
Holiday Home	59	62	68	66	65
Bed & Breakfast	198	198	202	193	186
Sum	461	469	480	473	475

Source: VisitPiemonte

Table A.A3: Impact of the share of empty apartments in 2011 on Airbnb Rooms

	(1)	(2)
Share Empty Apt. 2011	0.1094**	0.1094**
	(0.0447)	(0.0448)
Time FE	No	Yes
Obs.	231000	231000

Notes: the dependent variable is the number of Airbnb Rooms. Significance is indicated by * p<0.1. ** p<0.05, and *** p<0.001.

Table A.A4: Reduced Form - The impact of the IV variable on the number of licences

	(1) N° Category	(2) N° Category
Shift-Share	0.0001***	0.0001***
	(0.00005)	(0.00005)
Rent Control	No	Yes
Sociodem. Control	No	Yes
Spec/Div Control	No	Yes
Time FE	Yes	Yes
Cens FE	Yes	Yes
Category FE	Yes	Yes
Obs.	9417000	9417000

Notes: the dependent variable is the logarithm number of the licenses. The table reports the reduced form, namely the dependent variable on shift-share variable. Significance is indicated by * p<0.1. ** p<0.05, and *** p<0.001. Standard errors, in parenthesis, are clustered at census tract levels. The analysis takes place at the census tract-month level. Controls are grouped into i) Rent Control which accounts for the average commercial rent, ii) Sociodem. Control includes the population density, the share of foreign residents, the share of the population with age between 0 and 29 years, the share of the population with more than 66 years old, and the average number of families. iii) Spec/Div Control includes the Specialization and Diversity variables.

Table A.A5: IV baseline results by control composition

	(1) IV First St.	(2) IV Second St.	(3) IV First St.	(4) IV Second St.	(5) IV First St.	(6) IV Second St.	(7) IV First St.	(8) IV Second St.	(9) IV First St.	(10) IV Second St.	(11) IV First St.	(12) IV Second St.
Shift-Share	0.0305***		0.0301***		0.0295***		0.0310***		0.0306***		0.0300***	
	(0.0038)		(0.0038)		(0.0038)		(0.0037)		(0.0038)		(0.0037)	
N° Rooms		0.0046***		0.0080***		0.0051***		0.0041**		0.0088***		0.0046***
		(0.0017)		(0.0029)		(0.0018)		(0.0017)		(0.0029)		(0.0017)
Rent Control	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Sociodem. Control	No	No	Yes	Yes	Yes	Yes	No	No	No	No	Yes	Yes
Spec/Div Control	No	No	Yes	Yes	No	No	No	No	Yes	Yes	No	No
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	9471000	9471000	9471000	9471000	9471000	9471000	9471000	9471000	9471000	9471000	9471000	9471000
KP F-statistic	65.895		64.278		59.697		71.086		66.083		64.184	

Notes: in the even columns, the dependent variable is the logarithm number of economic licences, and in the odd ones the number of Airbnb rooms. Significance is indicated by * p<0.1. ** p<0.05, and *** p<0.001. Standard errors, in parenthesis, are clustered at census tract levels. The analysis takes place at the census tract-month level. Controls are grouped into i) Rent Control which accounts for the average commercial rent, ii) Sociodem. Control includes the population density, the share of foreign residents, the share of the population with age between 0 and 29 years, the share of the population with more than 66 years old, and the average number of families. iii) Spec/Div Control includes the Specialization and Diversity variables.

Table A.A6: Alternative tourism measure - Impact of tourism on establishment licenses

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	IV	IV	IV	IV	IV	IV	IV	IV
N° Airbnb	0.0002	0.0171**	0.0186**	0.0144**	0.0315**	0.0156**	0.0345**	0.0237**	0.0261**
	(0.0003)	(0.0071)	(0.0075)	(0.0059)	(0.0128)	(0.0061)	(0.0140)	(0.0096)	(0.0105)
Rent Control	Yes	No	No	Yes	No	Yes	No	Yes	Yes
Sociodem. Control	Yes	No	Yes	No	No	Yes	Yes	No	Yes
Spec/Div Control	Yes	No	No	No	Yes	No	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	9471000	9471000	9471000	9471000	9471000	9471000	9471000	9471000	9471000

Notes: the dependent variable is the logarithm number of Airbnb properties available and active. Significance is indicated by * p<0.1. ** p<0.05, and *** p<0.001. Standard errors, in parenthesis, are clustered at census tract levels. The analysis takes place at the census tract-month level. Controls are grouped into i) Rent Control which accounts for the average commercial rent, ii) Sociodem. Control includes the population density, the share of foreign residents, the share of the population with age between 0 and 29 years, the share of the population with more than 66 years old, and the average number of families. iii) Spec/Div Control includes the Specialization and Diversity variables.

Table A.A7: Impact of tourism on each category - Part 1

	(1) IV Objects	(2) IV Jewellery	(3) IV Fabrics/Rugs	(4) IV Laundry	(5) IV Pods Coffee	(6) IV Candies
N° Rooms	0.0285***	-0.0157	-0.0225***	-0.0003	0.0360***	0.0015***
	(0.0080)	(0.0112)	(0.0070)	(0.0024)	(0.0078)	(0.0024)
Rent Control	Yes	Yes	Yes	Yes	Yes	Yes
Sociodem. Control	Yes	Yes	Yes	Yes	Yes	Yes
Spec/Div Control	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Census FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	231000	462000	231000	231000	231000	231000

Notes: the dependent variable is the logarithm number of the licenses. The table reports the second stage. Significance is indicated by * $p<0.1$. ** $p<0.05$, and *** $p<0.001$. Standard errors, in parenthesis, are clustered at census tract levels. The analysis takes place at the census tract-month level. Controls are grouped into i) Rent Control which accounts for the average commercial rent, ii) Sociodem. Control includes the population density, the share of foreign residents, the share of the population with age between 0 and 29 years, the share of the population with more than 66 years old, and the average number of families. iii) Spec/Div Control includes the Specialization and Diversity variables.

Table A.A8: Impact of tourism on each category - Part 2

	(1) IV Hardware store	(2) IV Sexy shop	(3) IV Second Hand	(4) IV Optics	(5) IV Stationeries	(6) IV Cosmetics/Perfumery
N° Rooms	0.0114	0.0052**	-0.0225***	0.0122***	-0.0413*	-0.0173
	(0.0089)	(0.0022)	(0.0084)	(0.0045)	(0.0111)	(0.0115)
Rent Control	Yes	Yes	Yes	Yes	Yes	Yes
Sociodem. Control	Yes	Yes	Yes	Yes	Yes	Yes
Spec/Div Control	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Census FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	231000	231000	231000	231000	231000	231000

Notes: the dependent variable is the logarithm number of the licenses. The table reports the second stage. Significance is indicated by * $p<0.1$. ** $p<0.05$, and *** $p<0.001$. Standard errors, in parenthesis, are clustered at census tract levels. The analysis takes place at the census tract-month level. Controls are grouped into i) Rent Control which accounts for the average commercial rent, ii) Sociodem. Control includes the population density, the share of foreign residents, the share of the population with age between 0 and 29 years, the share of the population with more than 66 years old, and the average number of families. iii) Spec/Div Control includes the Specialization and Diversity variables.

Table A.A9: Impact of tourism on each category - Part 3

	(1) IV Motor/Car	(2) IV Sports Art.	(3) IV Mixed	(4) IV Food	(5) IV Health/Orthopedic Art.	(6) IV Automatic Machines
N° Rooms	-0.0034	0.0144*	0.0702***	0.1418***	0.0093*	0.0153***
	(0.0035)	(0.0080)	(0.0170)	(0.0259)	(0.0048)	(0.0050)
Rent Control	Yes	Yes	Yes	Yes	Yes	Yes
Sociodem. Control	Yes	Yes	Yes	Yes	Yes	Yes
Spec/Div Control	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Census FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	231000	231000	231000	231000	231000	231000

Notes: the dependent variable is the logarithm number of the licenses. The table reports the second stage. Significance is indicated by * $p<0.1$. ** $p<0.05$, and *** $p<0.001$. Standard errors, in parenthesis, are clustered at census tract levels. The analysis takes place at the census tract-month level. Controls are grouped into i) Rent Control which accounts for the average commercial rent, ii) Sociodem. Control includes the population density, the share of foreign residents, the share of the population with age between 0 and 29 years, the share of the population with more than 66 years old, and the average number of families. iii) Spec/Div Control includes the Specialization and Diversity variables.

Table A.A10: Impact of tourism on each category - Part 4

	(1) IV Home Art.	(2) IV Animals Art.	(3) IV Photography	(4) IV Tobacco	(5) IV Musical Inst.	(6) IV Extralimentary
N° Rooms	-0.0339***	0.0007	-0.0183***	0.0002	0.0053**	-0.1455***
	(0.0105)	(0.0090)	(0.0049)	(0.0054)	(0.0021)	(0.0256)
Rent Control	Yes	Yes	Yes	Yes	Yes	Yes
Sociodem. Control	Yes	Yes	Yes	Yes	Yes	Yes
Spec/Div Control	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Census FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	231000	231000	231000	231000	231000	231000

Notes: the dependent variable is the logarithm number of the licenses. The table reports the second stage. Significance is indicated by * $p<0.1$. ** $p<0.05$, and *** $p<0.001$. Standard errors, in parenthesis, are clustered at census tract levels. The analysis takes place at the census tract-month level. Controls are grouped into i) Rent Control which accounts for the average commercial rent, ii) Sociodem. Control includes the population density, the share of foreign residents, the share of the population with age between 0 and 29 years, the share of the population with more than 66 years old, and the average number of families. iii) Spec/Div Control includes the Specialization and Diversity variables.

Table A.A11: Impact of tourism on each category - Part 5

	(1) IV Forniture	(2) IV Pharmacy/Herb.	(3) IV Spare Accessories	(4) IV Games	(5) IV Fuels	(6) IV Hair./Beaut.
N° Rooms	0.0035	-0.0182***	-0.0034	-0.0002	-0.0168***	0.0930***
	(0.0099)	(0.0068)	(0.0068)	(0.0039)	(0.0052)	(0.0166)
Rent Control	Yes	Yes	Yes	Yes	Yes	Yes
Sociodem. Control	Yes	Yes	Yes	Yes	Yes	Yes
Spec/Div Control	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Census FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	231000	231000	231000	231000	231000	231000

Notes: the dependent variable is the logarithm number of the licenses. The table reports the second stage. Significance is indicated by * $p<0.1$. ** $p<0.05$, and *** $p<0.001$. Standard errors, in parenthesis, are clustered at census tract levels. The analysis takes place at the census tract-month level. Controls are grouped into i) Rent Control which accounts for the average commercial rent, ii) Sociodem. Control includes the population density, the share of foreign residents, the share of the population with age between 0 and 29 years, the share of the population with more than 66 years old, and the average number of families. iii) Spec/Div Control includes the Specialization and Diversity variables.

Table A.A12: Impact of tourism on each category - Part 6

	(1) IV Building Mat.	(2) IV Clothing	(3) IV Children Art.	(4) IV Libraries	(5) IV Hygiene House and Person
N° Rooms	0.0348***	-0.0513***	-0.0016	-0.0103	0.0010
	(0.0111)	(0.0150)	(0.0018)	(0.0082)	(0.0052)
Rent Control	Yes	Yes	Yes	Yes	Yes
Sociodem. Control	Yes	Yes	Yes	Yes	Yes
Spec/Div Control	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Census FE	Yes	Yes	Yes	Yes	Yes
Obs.	231000	231000	231000	231000	231000

Notes: the dependent variable is the logarithm number of the licenses. The table reports the second stage. Significance is indicated by * p<0.1. ** p<0.05, and *** p<0.001. Standard errors, in parenthesis, are clustered at census tract levels. The analysis takes place at the census tract-month level. Controls are grouped into i) Rent Control which accounts for the average commercial rent, ii) Sociodem. Control includes the population density, the share of foreign residents, the share of the population with age between 0 and 29 years, the share of the population with more than 66 years old, and the average number of families. iii) Spec/Div Control includes the Specialization and Diversity variables.

Table A.A13: Impact of tourism on clothing establishments

	IV
N° Rooms	-0.1297***
	(0.0464)
Rent Control	Yes
Sociodem. Control	Yes
Spec/Div Control	Yes
Time FE	Yes
Census FE	Yes
Category FE	Yes
Obs.	231000

Notes: the dependent variable is the logarithm number of the establishments with a surface ≤ than 250 squared meters. Significance is indicated by * p<0.1. ** p<0.05, and *** p<0.001. Standard errors, in parenthesis, are clustered at census tract levels. The analysis takes place at the census tract-month level. Controls are grouped into i) Rent Control which accounts for the average commercial rent, ii) Sociodem. Control includes the population density, the share of foreign residents, the share of the population with age between 0 and 29 years, the share of the population with more than 66 years old, and the average number of families. iii) Spec/Div Control includes the Specialization and Diversity variables.

Table A.A14: Impact of tourism on establishment licenses at the OMI and neighbourhood level

	OMI		Neighborhood	
	(1)	(2)	(3)	(4)
	IV	IV	IV	IV
N° Rooms	0.0009*	0.0008**	-0.0013	-0.0011
	(0.0005)	(0.0004)	(0.0008)	(0.0007)
Rent Control	No	Yes	No	Yes
Sociodem. Control	No	Yes	No	Yes
Spec/Div Control	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Category FE	Yes	Yes	Yes	Yes
Obs.	100860	100860	56580	56580

Notes: the dependent variable is the logarithm number of the licenses. The table reports the second stage. Significance is indicated by * p<0.1. ** p<0.05, and *** p<0.001. Standard errors, in parenthesis, are clustered at the OMI level in columns 1 and 2, and at the neighborhood level in columns 3 and 4. The analysis takes place at the census tract-month level. Controls are grouped into i) Rent Control which accounts for the average commercial rent, ii) Sociodem. Control includes the population density, the share of foreign residents, the share of the population with age between 0 and 29 years, the share of the population with more than 66 years old, and the average number of families. iii) Spec/Div Control includes the Specialization and Diversity variables.

Table A.A15: Impact of tourism on establishment licenses at different time unit

	Quarter		Semester	
	(1)	(2)	(3)	(4)
	IV	IV	IV	IV
N° Rooms	0.0043**	0.0039*	0.0020**	0.0030**
	(0.0019)	(0.0021)	(0.0016)	(0.0019)
Rent Control	No	Yes	No	Yes
Sociodem. Control	No	Yes	No	Yes
Spec/Div Control	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes
Census FE	Yes	Yes	Yes	Yes
Category FE	Yes	Yes	Yes	Yes
Obs.	3157000	3157000	1578500	1578500

Notes: the dependent variable is the logarithm number of the licenses. The table reports the second stage. Significance is indicated by * p<0.1. ** p<0.05, and *** p<0.001. Standard errors, in parenthesis, are clustered at the census tract level The analysis takes place at the census tract-month level. Controls are grouped into i) Rent Control which accounts for the average commercial rent, ii) Sociodem. Control includes the population density, the share of foreign residents, the share of the population with age between 0 and 29 years, the share of the population with more than 66 years old, and the average number of families. iii) Spec/Div Control includes the Specialization and Diversity variables

Table A.A16: Impact of tourism on local economic activities controlling for trends

	(1)	(2)
	IV - Tract and Category Trend	IV - Controls Trend
N° Rooms	0.0105*	0.0030*
	(0.0059)	(0.0051)
Rent Control	Yes	Yes
Sociodem. Control	Yes	Yes
Spec/Div Control	Yes	Yes
Time FE	Yes	Yes
Census FE	Yes	Yes
Category FE	Yes	Yes
Obs.	9471000	9471000

Notes: the dependent variable is the logarithm number of the licenses. The table reports the second stage. Column 1 includes Tracts and Licence Categories trends and Column 2 the control trends. Significance is indicated by * p<0.1. ** p<0.05, and *** p<0.001. Standard errors, in parenthesis, are clustered at the census tract level The analysis takes place at the census tract-month level. Controls are grouped into i) Rent Control which accounts for the average commercial rent, ii) Sociodem. Control includes the population density, the share of foreign residents, the share of the population with age between 0 and 29 years, the share of the population with more than 66 years old, and the average number of families. iii) Spec/Div Control includes the Specialization and Diversity variables

Table A.A17: Results with lagged explanatory variable

	(1) IV	(2) IV	(3) IV
N° Rooms t=-1	0.0045***		
	(0.0016)		
N° Rooms t=-2		0.0033***	
		(0.0011)	
N° Rooms t=-3			0.0026***
			(0.0009)
Rent Control	Yes	Yes	Yes
Sociodem. Control	Yes	Yes	Yes
Spec/Div Control	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Census FE	Yes	Yes	Yes
Category FE	Yes	Yes	Yes
Obs.	9313150	9155300	8997450

Notes: the dependent variable is the logarithm number of the licenses. The table reports the second stage. Significance is indicated by * $p<0.1$. ** $p<0.05$, and *** $p<0.001$. Standard errors, in parenthesis, are clustered at the census tract level The analysis takes place at the census tract-month level. Controls are grouped into i) Rent Control which accounts for the average commercial rent, ii) Sociodem. Control includes the population density, the share of foreign residents, the share of the population with age between 0 and 29 years, the share of the population with more than 66 years old, and the average number of families. iii) Spec/Div Control includes the Specialization and Diversity variables

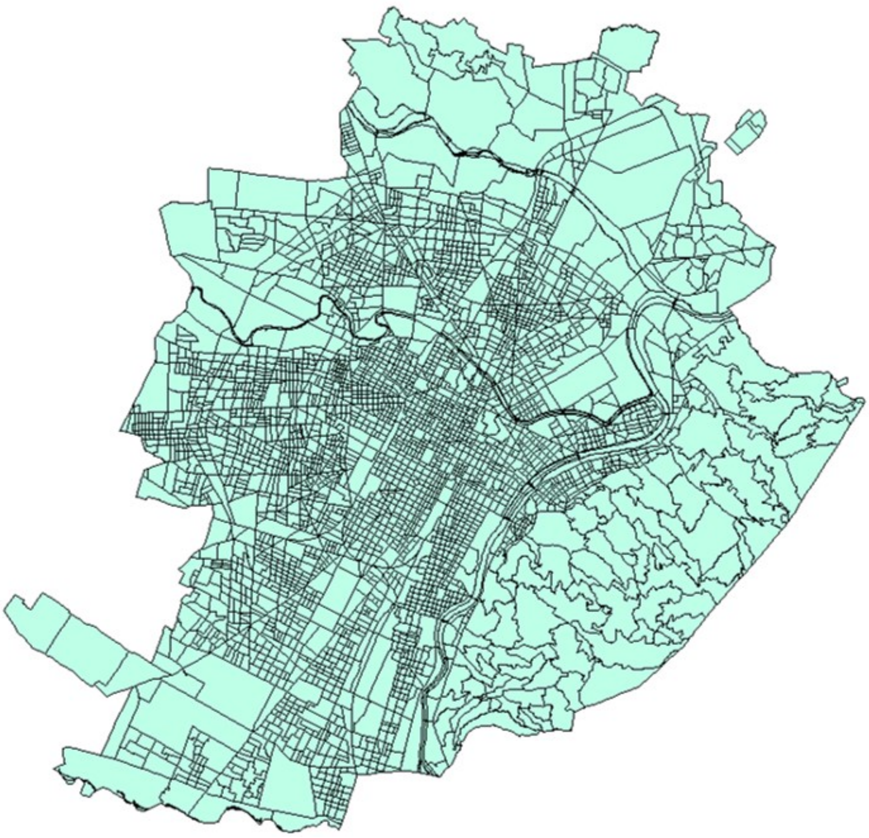
Table A.A18: Impact of tourism on the local economic activities with reduced sample

	(1) IV	(2) IV
N° Rooms	0.0446***	0.0163***
	(0.0022)	(0.0036)
Rent Control	No	Yes
Sociodem. Control	No	Yes
Spec/Div Control	No	Yes
Time FE	Yes	Yes
Census FE	Yes	Yes
Category FE	Yes	Yes
Obs.	7220100	7220100

Notes: the dependent variable is the logarithm number of the licenses. The table reports the second stage. Significance is indicated by * p<0.1. ** p<0.05, and *** p<0.001. Standard errors, in parenthesis, are clustered at the census tract level The analysis takes place at the census tract-month level. Controls are grouped into i) Rent Control which accounts for the average commercial rent, ii) Sociodem. Control includes the population density, the share of foreign residents, the share of the population with age between 0 and 29 years, the share of the population with more than 66 years old, and the average number of families. iii) Spec/Div Control includes the Specialization and Diversity variables

Figures

Figure A.A1: Turin census tracts

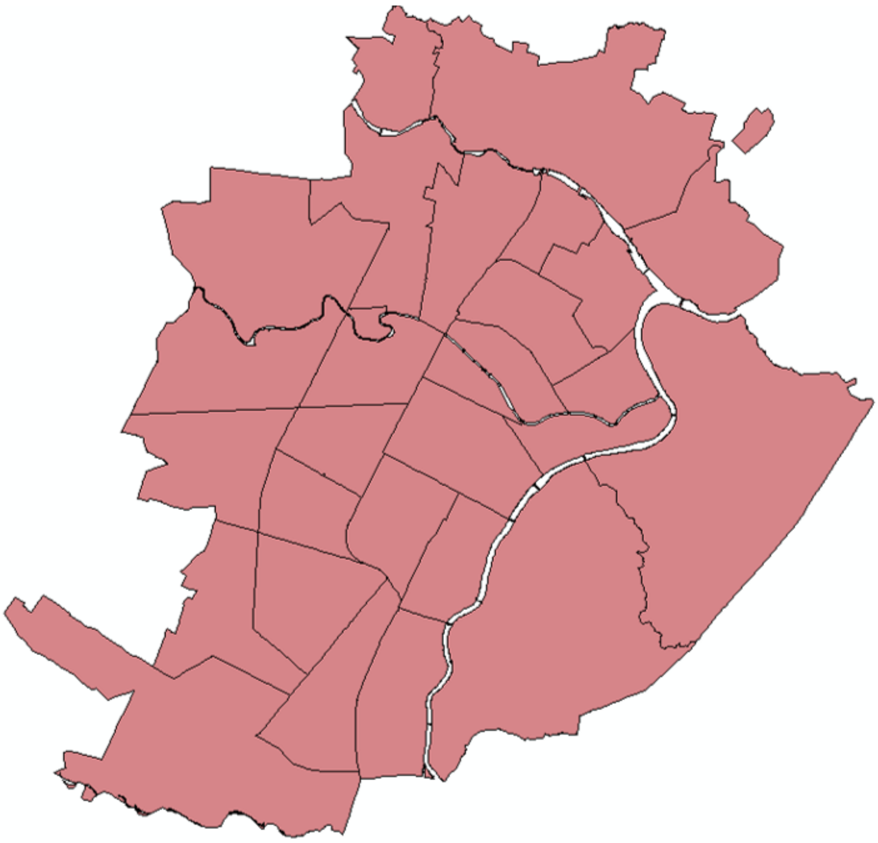


Notes: This graph plots Turin divided in census tract. The census tracts are 3850.

Figure A.A2: Turin OMI zones

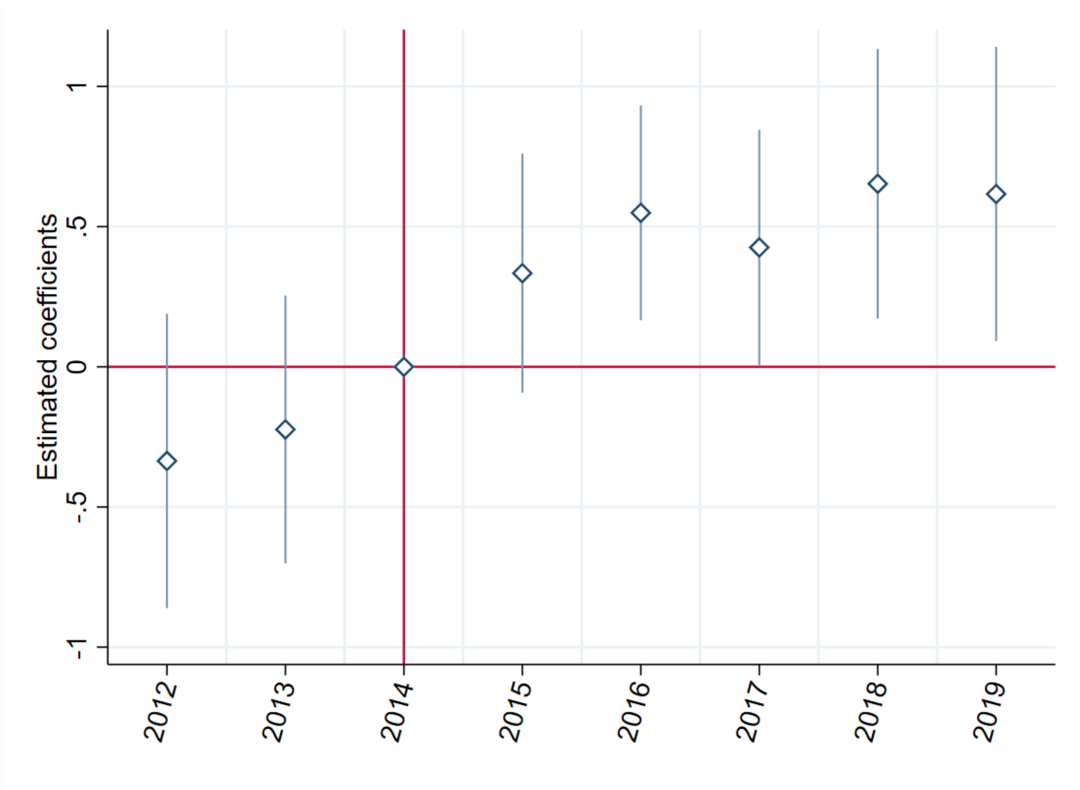
Notes: This graph plots Turin divided into OMI areas. The OMI areas are 63.

Figure A.A3: Turin neighborhood



Notes: This graph plots Turin divided into neighbourhoods. The neighbourhoods are 23.

Figure A.A4: Dynamic Effects - The Logarithm of the number of licences on the share of empty apartment in 2011



Notes: Standard errors are clustered at the census tract level. The event study includes control variables, namely i) Rent Control which accounts for the average commercial rent, ii) Sociodem. Control includes the population density, the share of foreign residents, the share of the population with age between 0 and 29 years, the share of the population with more than 66 years old, and the average number of families. iii) Spec/Div Control includes the Specialization and Diversity variables.

Figure A.A5

Notes: Green tracts are those included in the sample for the robustness check. White areas are contiguous to neighborhood borders, therefore are excluded from the sample for the robustness check.