Urban Amenities and Tourism: Evidence from TripAdvisor

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Abstract

Using TripAdvisor reviews, we construct panel data on tourism and consumption in Paris. We document that during the pandemic a drop in tourism caused an increase in Parisians' satisfaction with restaurants and other amenities. Among three mechanisms — overcrowding, supply-side changes and aversion towards tourists — we only find support for the latter. During the pandemic the word 'tourist' became less frequent in reviews, while other words relating to food quality, price and overcrowding stay on the same level. The improvement in ratings was stronger in restaurants popular among tourists from countries with weaker social ties to France. **JEL classification:** O18, L83

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1 Introduction

"Are there too many tourists in Paris?" – was a title of the conference organised by the city hall of Paris on June 24, 2019. While the speakers of the conference agreed that overtourism in Paris has not yet reached the same scale as in Amsterdam or Barcelona, they also admitted that "rapid and poorly regulated growth" of tourism can be harmful to the city[1]. There were reasons for concern. The number of foreign tourists to France has more than doubled over the previous 15 years. In 2019 France was the most visited country in the world, and Paris was the third most visited city. During the year 35.4 million tourist stayed in the city's hotels, which is approximately 16 times more than the population of Paris.

In the years preceding the pandemic, concerns about tourism have became common in Europe.[2] Anti-tourist protests took place in Barcelona, San Sebastián, Mallorca, Venice and other European cities. Anti-tourist graffities, typically saying "tourist go home", were spreading across the cities including Paris.

However, during the summer of 2020, there were no crowds of tourists in Paris. The problem of overtourism raised at the city hall conference faded into the background, when the COVID-19 pandemic and the stringency measures, imposed by the governments, disrupted tourist inflows, causing, as was coined by the World Tourism Organization, "the worst year in tourism history".

It is still unclear what the tourism industry will face after the pandemic: whether it will continue to grow at the pre-pandemic rate, slow down or start to shrink. While the industry is on hold, the questions posed by researchers and policy-makers before the pandemic remain relevant and open. What is an optimal level of tourism? What are its costs and benefits? At the same time, the unexpected shock in tourism created a proper setting to explore the question: "What would life be for residents of Paris if there were no tourists?" In fact, during the summer of 2020 Parisians were not bothered by an excess of tourists, while restaurants and other urban amenities remained accessible, and COVID-19 cases and deaths were relatively low, as the first pandemic wave was fading out. In addition, restaurants were kept open artificially through heavy government subsidies, providing a unique setting to study demand-related factors without an endogenous adjustment of supply.

In this paper we estimate the effect of tourism on residents' satisfaction with restaurants and other urban amenities. We use data on restaurant reviews from Tripadvisor – the platform that aggregates user-generated content on restaurant and other travel experiences. We construct unique panel data on consumption and amenities in the city. This data allows us to achieve multiple goals at the same time.

First, we use it to produce a highly granular measure of tourism. The share of non-French among all reviews serves as a close proxy of tourists' presence, which we validate using several other measures. The benefit of this measure is that it can be defined on a very granular level, the restaurant itself. In addition, while many studies focus on the location where tourists stay

[1] See CNews. The World Tourism Organization (UNWTO) defines overtourism as "the impact of tourism on a destination, or parts thereof, that excessively influences perceived quality of life of citizens and/or quality of visitor experiences in a negative way" (Carvão et al., 2018). For a review on overtourism from the tourism management literature see Capocchi et al. (2019).

[2] See the Guardian

overnight to study the impact, the measure used here allows to study the location of where tourists consume.

Second, the review data and the ratings given by locals can be used as an indicator of locals' satisfaction with restaurant experience. More generally, it serves as a measure of satisfaction with urban amenities, which varies across space and time. The literature shows that this indicator is meaningful: For example, Kuang (2017) finds that restaurant ratings are highly correlated with real estate prices.

We match restaurant data with another source of information on residents' quality of life: number of complaints on the crowd-sourced platform DansMaRue. The platform is provided by the city hall of Paris. Users can report any problem related to public space (abandoned waste, tags, wild posting, etc.) through the mobile application or the web-site. Then the city administration analyses the reports and try to solve the problems. We treat this disamenity measure as another outcome relevant to our study.

We first document two stylized facts. First, more touristic restaurants receive lower ratings by locals in the cross-section, suggesting a potential disamenity stemming from tourist demand. Second, touristic neighborhoods have a lower variety of amenities which may indicate that tourists value variety less than locals do.

Using the pandemic as a source of exogenous variation in international tourist arrivals, we find that the drop in tourism caused an increase in residents' satisfaction with urban amenities, both in terms of restaurant ratings and a decreased number of complaints on *DansMaRue*. In particular, the average restaurant increases its rating by close to 10% of a standard deviation in the absence of tourists and the number of complaints in the direct vicinity of the average restaurant decreases by at least 8%.

Importantly, our effect is not unique to the lockdown-induced tourism decline. We find similar evidence when using the terrorist attacks that took place in November 2015. Our results are also robust to using measures of tourism that are based on the self-declared location of users rather than language.

Next, we consider three potential mechanisms driving our findings: overcrowding, supply-side change and residents' aversion towards tourism. Our analysis only finds support for the aversion mechanism. First, we find that the number of reviews explicitly mentioning tourism (which are often negative) declines. Second, relying on a proxy of social connectedness between countries derived from Facebook data, we find that restaurants with a clientele that has little connections to France sees a larger increase in its rating post-lockdown. This suggests that Parisians are less bothered by tourists from countries with which they have strong social ties.

This study is most closely related to a growing literature studying the interaction of tourism and local amenities. Allen et al. (2020) study the effects of tourism on residents' welfare in Barcelona. Building on a quantitative spatial model and credit card expenditure data, they derive the incidence of tourism on locals' welfare and find a largely heterogeneous impact which negatively affects those living in the center, while resulting in welfare gains for those living in less central parts of the city. While they are able to quantify the welfare effects of tourism, our paper focuses on how tourism affects the reported satisfaction with the quality of specific amenities and highlights the channels through which tourism operates.

This paper is also related to the literature on endogenous amenities. In contrast to historical sites and natural landmarks, endogenous amenities such as restaurants and bars are reactive to demand. In particular, Almagro and Domınguez-Iino (2019) study how amenities and location sorting by residents endogenously adjust to a large increase in tourist demand, focusing on the city of Amsterdam. Relative to their paper, we focus on relatively short-term effects where amenities and residence location are essentially fixed.[3]

More generally, our paper builds on the literature emphasizing the importance of amenities. In their seminal paper Glaeser et al. (2001) explore the role of cities as centres of consumption. They show that high-amenity cities have been growing faster than low-amenity cities, highlighting the importance of amenities for location choices. Generally, on the importance of urban amenities for attracting residents see also Carlino and Saiz (2019), Lee (2010) and Couture and Handbury (2020).

This paper is not the first to use data on restaurant reviews to study urban amenities. Kuang (2017) argues that quality of urban amenities are important for city residents, which is revealed in real estate prices. She measures the quality of amenities using restaurant ratings posted by users on Yelp.

It is worth noting that tourism can have a substantial positive economic impact, and tourism suspension causes deep economic damage to the local economy (see e.g. Faber and Gaubert (2019)). This paper does not focus on the direct effects of tourism on the local economy, but rather its impact on local amenities.

Finally, this paper belongs to the growing and diverse literature on the COVID-19 pandemic and its interaction with the urban structure (Gupta et al., 2021; Althoff et al., 2020; De Fraja et al., 2020; Miyauchi et al., 2021; Couture et al., 2021; Gupta et al., 2020; Coven et al., 2020).

2 Background and Data

In this section we first discuss how in the summer of 2020 the Covid-19 pandemic led to a sharp drop of tourists coming to Paris, while there were few restrictions for locals. Next, we discuss our main dataset on restaurant reviews that were collected from the website Tripadvisor and additional datasets from other sources that we use.

2.1 COVID-19 in Paris

The first restrictions related to Covid-19 took effect in early 2020. On March 12, Emmanuel Macron announced in a televised address that all schools and universities across France would be closed. On March 13, 2020, Prime Minister Edouard Philippe announced the closure of all pubs, restaurants, cinemas and nightclubs. After three months of strict lockdown measures, on June 14, cafes, restaurants and pubs reopened in Paris.

While the restaurant sector returned to normality, tourism remained heavily affected by the global pandemic. The Ile-de-France region which encompasses Paris was especially heavily hit.

[3] The government was essentially freezing the local economy through heavy subsidies.

Relative to July 2019, it saw a drop of 70.8% in overnight stays in its hotels in July 2020[4]. The following months saw a similar drop in demand in the hospitality sector. This drop was especially pronounced among tourists not residing in France. Compared to 2019, France saw 71.8% less non-residents in overnight stays in 2020, whereas overnight stays by residents declined only by 10.5%. To summarize, Paris saw a large drop in tourism in the summer of 2020 which was mainly concentrated in international arrivals.

2.2 Tripadvisor Data

Tripadvisor is a user-generated social media review site, which publishes user reviews on restaurants, hotels and other attractions. We collected data on all Parisian restaurants that were listed on the site on November 17, 2020.[5] We obtained information on restaurant characteristics, such as the type of cuisine and the address, and individual review data, including the review's date, text, language, user, user location and rating. We geocode restaurants' addresses. We leverage the data on review's language and user location to separate consumption of residents and tourists. As a result we construct unique and highly detailed panel that reflects city's restaurant consumption across space and time.

Figure 1 presents the daily number of reviews of the roughly 15,000 Parisian restaurants, cafes and bars left on the platform since its launch. The time trends are represented by smoothing splines. Reviews are split into two categories: reviews written in French and written in other languages. The figure shows both the process of technology adoption and the fluctuations in restaurant consumption. French users began adapting the platform in 2007, and their usage peaked in 2017.

Figure 2 zooms in the same time series to a period starting from 2018 when the platform's penetration is relatively stable. The beginning and the end of the "first-wave" lockdown imposed by the French government are marked with a blue dotted line. During the lockdown both French and non-French reviews dropped to near zero. Then, starting in June, French reviews revived, but foreign reviews remained on a negligible level. The observational period ends with both French and non-French review numbers going back to zero due to the introduction of a second wave of restrictions. As a whole, these figures demonstrate that the review data allows us to differentiate between demand by residents and tourists.

2.3 Measuring Tourism

In this paper we use review data to construct a highly granular measure of tourism at the restaurant level. Importantly, it gives us an indicator of where tourists consume in the city rather than where they stay. Our preferred proxy of tourism is constructed as a share of reviews written in languages other than French. In Section B.2 in the Appendix we repeat our analysis using an alternative measure of tourism based on users' home locations.

[4] See INSEE FOCUS No. 235 here https://www.insee.fr/fr/statistiques/5369851#consulter

[5] In this analysis, we restrict ourselves to restaurants located in Paris *intra-muros* – the city of Paris that consists of 20 municipal arrondissements and excludes the surrounding Greater Paris area.

The Figure 3 shows a map of our tourism measure. A lighter color indicates a higher share of non-French reviews. As expected, restaurants with the highest levels of tourism are located in the areas known for Paris' major attractions: the Eiffel tower, Montmartre, Notre-Dame de Paris and the Arc de Triomphe.

To validate our proxy for tourism more formally, we use data from the *Enquêtes de fréquentation des sites culturels* provided by the *Observatoire économique du tourisme parisien* (Observatory of the Parisian tourism economy). This survey contains the share among all tourists coming to Paris visiting different tourist attractions. We consider tourists visiting from 2015 to 2019 and geocode the 18 attractions that are located intra-muros contained in the survey. Then, we construct a measure for demand by tourists that follows the market access framework widely used in the economic geography literature:

$$\text{Tourist Access}_i = \sum_j \frac{\text{Visitors}_j}{\text{Distance}_{ij}}$$

Note that we are implicitly assuming a distance elasticity of tourist consumption trips of -1. While we are not aware of a paper estimating this parameter specifically for demand by tourists, Miyauchi et al. (2021) look at the distance elasticity of location choice for consumption trips. They find a value of -1.09 and thus close to -1.

Next, we correlate our tourism proxy with the tourist demand measure. As Figure 5 shows, we find a strong positive correlation between the two (the R^2 of a linear regression is 0.19). The correlation is robust to controlling for quartier fixed effects, meaning that, even after controlling for a relatively fine-grained spatial unit, the remaining variation in our tourism proxy is correlated with tourist access (see Table C.1). Together, this shows that our proxy for tourism correlates strongly with other, external measures of tourism.

Finally, to further corroborate our proxy for tourism, we rely on user location information. In particular, we compute the share of users by restaurant who indicate a location in a country other than France. As figure A.2 shows, the two measures are highly correlated (the R^2 of a linear regression is around 0.77).

2.4 Content of Reviews

We perform text analysis of reviews to better understand users' concerns. We distinguish five topics that are relevant to the mechanisms we want to test for: discussion on tourism, concerns about low food quality, high price, long waiting time and noisy environment.

The mapping of the review texts to topics is determined by manually constructed dictionaries. The procedure of constructing the dictionary is the following. First, we examined around one thousand randomly selected reviews to find a sample of words that relates to the topic in a non-ambiguous way. Second, we validate these terms searching for counter-examples in the corpus – the "false-positives", the reviews where these terms are mentioned, but in fact these reviews are not related to the topic. Third, we extend our dictionary with common misspellings of the selected terms. We also take partial forms of the words. Lastly, we we create a list of 'minus' phrases, so that wordings such as *"pas cher"* (not expensive) will not be flagged as *"cher"* (expensive).

Overall , our approach minimises false positives (the probability that the text is attributed to the topic, when in fact it is not related to the topic), but is does not minimise *false negatives* (the probability that the text is not attributed to the topic, when in fact it is related to the topic). The short version (without misspellings and versions) of our dictionary is presented in the Table D.1. The summary statistic of topics is presented in the Table D.2. Notably, all topics occur with relatively similar frequency (between 2% and 6%) and thus allow a meaningful comparison.

2.5 Dans Ma Rue

Most of our analysis is based on the TripAdvisor data. To externally validate that our the presence of tourists affects locals' satisfaction with amenities, we draw on an additional dataset from the application *Dans Ma Rue* created by the Municipality of Paris. With the help of this application, citizens can register and geolocalise 'anomalies' observed in public space in Paris.[6] Users upload the complaints directly from their smartphones, specifying the location, date and the subject. The aim of the application is to improve the quality of Parisian public space by giving access of user-generated data on 'anomalies' to municipal service. The application was launched in 2012. For our analysis we focus on complaints about commercial activity which is the category most related to restaurant activity.

The high resolution of the data allows us to only consider complaints that are possibly related to a particular restaurant. We assign complaints to a given restaurant within a 100m radius.

2.6 Social Connectedness Index

Below we want to test whether the origin of tourists has an impact on locals' perception of them. To proxy for cultural proximity between foreign countries and France we rely on the Social Connectedness Index (SCI) published by Facebook.[7] It is based on the number of Facebook friendships between users located in a pair of countries. More precisely, it is computed as

$$\text{Social Connectedness}_{ij} = \frac{\text{FB Friends}_{ij}}{\text{FB Users}_i \times \text{FB Users}_j}$$

where FB Friends_{ij} are the number of friendships between users residing in countries i and j and FB Users_i the number of users in country i. For further details on the methodology see Bailey et al. (2018). Relying again on the information on users' origin, we compute the average social connectedness between the French population and the non-French customers of a particular restaurant.

[6] The set of potential 'anomalies' includes overflowing litter bins, illegal graffiti, abandoned objects, road damage and many others.

[7] The version we use dates from October 2021.

3 Stylized Facts

This section presents stylized facts about the geography of tourism in Paris.

More touristic restaurants receive lower ratings.

To compare the perceived value of more and less touristic places, we run the following regression at the review level

$$\text{Rating}_{rij} = \beta \text{Tourism}_j + X_j + \gamma_i + \epsilon_{rij} \tag{1}$$

where Rating_{rij} is the rating given by user i for restaurant j in review r. Our variable of interest is Tourism_j which is a measure of how touristic restaurant j is. We add other controls at the restaurant level (X_j) and control for user-level fixed effects (γ_i). This means we are comparing different reviews made by the same user, controlling for all unobservables at the level of the user. We also estimate a variation of this specification with quartier fixed effects. This captures any geographic amenity shifter, e.g. restaurants located along the river Seine receiving systematically higher ratings because of a nice view. We cluster standard errors at the restaurant level.

Table 1 displays the results of estimating equation 1. The estimation is based on pre-Covid data in order to avoid any confounding effects. We estimate the regression separately for Parisians only, since we are interested in the value of amenities for the local population. We find that overall more touristic places receive lower ratings ($\beta < 0$), after controlling for the (log) number of reviews received by the restaurant and for user and grid cell fixed effects. Using the most stringent specification with quartier-level fixed effects in column 3, we find that an increase in tourism demand by one standard deviation is associated with a rating that is around 2% lower[8].

More touristic neighborhoods have less diverse restaurants

While more touristic venues seem to receive lower ratings, we also find that tourism systematically correlates with other characteristics of neighborhood amenities. We start from the idea that tourists often visit foreign places to get an impression of the local culture. Thus, local businesses may cater to this demand by offering a version of French culture that is particularly appealing to tourists. Indeed we find that the share of restaurants offering French cuisine is much higher than in neighborhoods more dominated by locals (see figure 6).

To capture diversity more broadly, we compute the market share of each cuisine type (weighted by the number of reviews). We then compute the Herfindahl index and show that more touristic areas have a systematically more concentrated market for restaurants (see figure 7). This illustrates that tourism is associated with a less diverse set of amenities.

[8] The standard deviation of tourism intensity is around 0.125 and the mean rating is around 3.82

4 Empirical Strategy

We employ a standard difference-in-differences framework at two different levels of aggregation to study the impact of the absence of tourists on locals' valuation of amenities. First, a restaurant-level approach gives us a broad picture of whether more and less touristic venues evolved differently over time. Second, review-level regressions allow us to asses whether the same users evaluated initially more touristic restaurant differently when borders were closed.

4.1 Restaurant-level Approach

At the restaurant level, we use the following specification

$$\mathrm{Y}_{jt} = \beta \times \text{Post-Lockdown}_t \times \text{Tourism}_j + \gamma_j + \delta_t + \epsilon_{jt} \tag{2}$$

where Y_{jt} is an outcome of restaurant j in month t. Post-Lockdown$_t$ is a binary variable indicating whether month t belongs to the post-lockdown period. Tourism$_j$ measures to what extent restaurant j is frequented by tourists. We include restaurant fixed effects (γ_j) and month fixed effects (δ_t). In a more stringent variation of this specification we also include quartier-time fixed effects. This controls for any unobserved time-varying factors at the neighborhood level, such as an increased share of remote working that may affect residential neighborhoods differently than the business district. Standard errors are clustered at the quartier level.

Below we will focus on one main outcome. We look at the average rating that restaurant j receives in month t, only looking at reviews by local residents. Our hypothesis is that tourism lowers the utility locals derive from amenities (visiting a restaurant in our case). We thus expect $\beta > 0$.

4.2 Review-level Approach

At the review level, we use the following specification

$$\mathrm{Y}_{ijt} = \beta \times \text{Post-Lockdown}_t \times \text{Tourism}_j + \gamma_j + \delta_t + \mu_i + \epsilon_{ijt} \tag{3}$$

where Y_{ijt} is a rating by user i for restaurant j in month t. As above, Post-Lockdown$_t$ is a binary variable indicating whether month t belongs to the post-lockdown period. Tourism$_j$ measures to what extent restaurant j is frequented by tourists. In addition to restaurant and month fixed effects (γ_j, δ_t), we also include user fixed effects, relying on within-user changes pre- to post-lockdown. Again, we cluster standard errors at the quartier level.

While including user fixed effects is already restrictive, identification can still come from comparing the magnitude of within-user changes across users, depending on whether they visited a touristic restaurant or not. If e.g. an increased life satisfaction post-lockdown and the propensity to visit more touristic restaurants were both determined by an unobserved third factor, our findings would be spurious. We thus, in a final step, interact user fixed effects with a post-lockdown dummy. This restricts identification to users who review at least two restaurants either before or after the lockdown. Intuitively, this specification captures whether the penalty for more touristic places decreased after the lockdown relying only on different ratings for more or less touristic restaurants by a user in the same period.

Our parameter of interest is β. Our hypothesis is that tourism is bad for locals' utility derived from a restaurant visit. Hence, we should observe that post-lockdown, when restaurants were open, but tourists were not present, initially touristic places start receiving higher ratings ($\beta > 0$).

5 Results

Table 2 shows the results of estimating equation 2 using the average monthly rating by Parisians at the restaurant level as the outcome variable. [9] We find that initially more touristic venues receive higher ratings when tourists are no longer around. Importantly, the effect is not driven by neighborhood-level trends as including quartier-time fixed effects only marginally changes the coefficient.

The magnitude of the coefficient can be best understood when considering the average tourism share of around 31.6%. The estimate in column 2 then implies that in Paris without tourists, which comes close to the reality of the post-lockdown summer, locals rate the average restaurant around 0.1 (or around 8% of a standard deviation) higher. At the 90th percentile of the tourism share this estimate more than doubles to around .22 (or around 17% of a standard deviation).

Table 3 shows the results of a user-level estimation (see equation 3). Importantly, this econometric approach allows us to exploit within-user changes in behavior while holding fixed time-invariant characteristics, such as preferences for certain types of neighborhoods or restaurant types. We confirm our results at the user level, i.e. Parisians rate their experience higher in places previously frequented by many reviewers not from Paris. The coefficient is of similar magnitude as at the restaurant level.

6 Robustness & Further Results

In this section we first present results using the data on neighborhood complaints as a different measure of disamenities. Then, we show that our result is not specific to the pandemic-induced shock to tourism, not driven by pre-trends, not affected by spillovers and present minor robustness exercises such as different levels of clustering.

6.1 Neighborhood Complaints

So far we have focused only on data coming from *Tripadvisor*. To provide further evidence that the lower influx of tourists improved locals' perceived satisfaction with local amenities, we analyze data on complaints registered within 100m of the restaurants in our sample by local

[9] Note that the sample is thus constrained to restaurants that receive at least one rating by a Parisian in a given month.

residents (see 2 for a detailed description). The goal of this exercise to show that tourism not only affects people going to restaurants but also local residents.

We estimate equation 2, replacing the average rating of the restaurant with the number of complaints in the vicinity of a restaurant within a given month. As this is a count variable which contains zeros, we use a Poisson model to estimate this equation.

Table 4 presents the results. We find that complaints around touristic restaurants decline relative to less touristic ones. Using the most conservative estimate in column 2, complaints around a restaurant with an average share of tourists among its customers decrease by around 8%.[10]

The positive impact of a decrease in the arrival of tourists is thus not only reflected in restaurant ratings, but also confirmed by an entirely external data source, namely crowd-sourced complaints that are used to improve municipal services.

6.2 Bataclan Attacks

We exploit the Covid-19 pandemic as an exogenous shock to tourism. However, the pandemic also affected the mobility of residents and thus the spatial mobility patterns in the city. While there were little restrictions in place during the summer of 2020, some people continued to work from home. In the empirical analysis above we control for trends that happen at the level of neighborhoods. Thus, a general shift in where the working population consumes is controlled for. In addition, we present results at the user level, thereby abstracting from compositional changes in the restaurants' visitors.

Still the pandemic may have affected restaurants in ways that are unobservable to us and correlated with our measures of tourism. For example, restaurants with larger outdoor facilities may have benefited most after the lockdown was lifted, as people continued to be cautious because of the risk to get infected. If the availability of outdoor facilities is correlated with our measure of tourism, we are wrongly attributing the observed changes in ratings and demand to tourism.

To alleviate concerns related to the specific nature of the pandemic, we instead use the the terrorist attacks that took place on November 13, 2015 as an exogenous shock to tourism. Three groups launched a total of six attacks that day in Paris, killing 130 people. These gruesome attacks shocked France and were widely covered in the international press. In the months that followed, Paris saw a strong decline in tourism. Occupancy rates were down by 13.1% in the three months following the attacks compared to the same period in the year before.[11]

Table B.1 display the results of estimating equation 2 using reviews from January 2015 to June 2016 and defining tourism intensity based on data from 2014. November 2015 is dropped from the analysis and December 2015 onwards is defined as post-Bataclan. We find that initially more touristic restaurants received better ratings by Parisians after the November attacks. Compared to table 2, the coefficient is substantially smaller which is in line with a lower drop

[10]We use the average tourism share of 31.6% and multiply it with the coefficient in column 2.

[11]See https://www.costar.com/article/724916287 for reporting on the impact of terrorist attacks on hotel occupancy rates.

in tourism arrivals than during the summer of 2020. Overall, this very different natural experiment lends support to our hypothesis that tourism negatively affects the quality of amenities as perceived by locals. This does not seem to be driven by factors specific to the pandemic.

In addition, the November attacks allow us to look at the reaction of reviewers that are not from Paris. Interestingly, there is no effect on their ratings of touristic places. This suggests that the externalities caused by tourism specifically affect locals.

6.3 Pre-Trends

In order to asses the timing of the effect that we find, we estimate equation 2 allowing for β to be time-varying. In particular, we estimate one coefficient per quarter and set the first quarter of 2020 as reference group. If the effect is driven by the sudden and unexpected absence of tourists due to the pandemic, we should observe no differential trends for more touristic restaurants prior to the outbreak of Covid-19. Figure 8 plots the estimated coefficients along with 90% confidence intervals. The figure shows that prior to the Covid-19 outbreak coefficients are close to and not statistically different from zero. Then, in Q3 and Q4 of 2020 coefficients are positive and statistically different from zero. This lends further support to the interpretation that Covid-19 led to a shift in locals' ratings of touristic venues.

6.4 Spillovers

The analysis is focused on tourists visiting a particular restaurant. We thus far have not tested if this effects spills over to restaurants located close by. In this case the effect of tourism would be further amplified. We thus include in our baselin specification, equation 2, measures of many tourists visit restaurants in the surrounding area. As table 8 shows, using different distances, we do not find strong evidence for that. The impact of a reduced influx of tourists seems to be mostly limited to the restaurant itself.

6.5 Further Robustness Checks

In order to lend further credibility to our main result we perform several robustness exercises. First, we report our main result clustering standard errors at different levels. As table B.6 shows, clustering at the quartier level as done throughout our analysis is on the conservative side. Second, we use different measures of tourism. In table B.5 we vary the period over which we compute the initial tourism share. Again, our results are robust to these different permutations. Third, we use the share of reviews left by non-Parisians instead of the share of reviews not written in French. As table B.2 illustrates, using this different proxy results in a qualitatively similar effect.[12]

[12]Note that this measure likely also captures domestic tourism. Since travel restrictions mainly applied to international visitors, we focus on the share of non-French reviews below.

7 Mechanisms

To get at the mechanism, we use two different approaches. First, we use the text-based classification of reviews described in section 2. In particular, we estimate the following equation

$$\text{Share Reviews}_{jt} = \beta \times \text{Post-Lockdown}_t \times \text{Tourism}_j + \gamma_j + \delta_t + \epsilon_{jt} \tag{4}$$

where Share Reviews_{jt} is the share of reviews of restaurant j in month t referring to a particular type of topic, such as overcrowding.[13] The rest of the specification is as described in section 4. We also estimate a review-level version of this specification. The results are displayed in table 5.

Second, we split the coefficient on the tourism-post interaction by variables defined at the restaurant level. This allows us to see if the effect is driven by certain types of restaurants.

Below, we will discuss three main mechanisms: overcrowding, supply-side changes and a direct aversion against the presence of tourists.

7.1 Overcrowding

A long waiting time and a noisy environment are distinctive features of overcrowding. Congestion caused by tourists should lead to an in increase of frequencies of these topics. As table 5 shows, we find no evidence pointing in this direction. More touristic restaurants did not receive relatively less reviews mentioning a long wait or noise after the lockdown. We interpret this as congestion not being a major driver of our results.

7.2 Supply-Side Changes

Low quality of food can be associated with the supply-side mechanism. According to this mechanism, restaurants change their technology when they are oriented to the tourist market – automatize the production, but also decrease the quality perceived by residents, since in this case the restaurants face lower incentives to provide consistent quality (tourists are not repeat consumers). This tendency should reflect in reviews left by residents. A similar logic can be applied to the concerns of too high prices. When consumers say that the price is too high, it likely means that price does not correspond to the perceived quality of the product.

7.3 Aversion

Another driver of our results could just be a direct, taste-based aversion of locals against tourists, closely linked and probably not distinguishable of xenophobia. As table 5 shows, the only reviews that explicity meantion tourists appear significantly less after the lockdown in initially touristic places. This suggests that it is something about the presence of tourists themselves rather than perceived overcrowding or decreases in quality.

[13]Similarly, we estimate equation 3 with a dummy as dependent variable indicating whether a topic is mentioned in the review or not.

To further test whether a direct aversion against the presence of tourists is at play, we test whether the increase in ratings is higher when the tourists are socially more distant to the local population. In particular, we exploit the information on users' origin provided in their profile. This allows us to compute for each restaurant the share of reviewers from a given country of origin. We combine this with the Social Connectedness Index (SCI) to compute the average SCI between restaurants' foreign reviewers and France.[14]

If Parisians have a distaste for foreigners from less familiar countries, we should see a higher increase in satisfaction for restaurants with many visitors from these countries. We thus estimate the treatment effect separately for restaurants with above and below-median SCI value. Table 6 shows that the increase in ratings of touristic places is indeed driven by low-SCI restaurants. For example, in column 4, the treatment effect for high-SCI is close to and not statistically different from zero. The coefficient for low-SCI places on the other hand suggests that touristic, low-SCI restaurants increased their average rating by around 0.13. This evidence is thus consistent with homophily among locals.

One concern might be that social connectedness is correlated with actual tourist arrivals from a country during the post-lockdown summer. However, the nature of the shock is such that arrivals from all countries drop to almost zero. Identification is thus almost entirely based on the pre-Covid exposure to tourism. In unreported results we control for differential changes in demand by nationality using a Bartik-style shock and find almost no change in our estimates.

8 Conclusion

This paper studies the impact of tourism on a key urban amenity, restaurants. Exploiting a large decline in international travel during the Covid-19 pandemic, we find that tourism decreases the perceived quality of restaurants among locals. We find suggestive evidence that the negative effect of tourism operates through direct aversion against the presence of tourists, rather than overcrowding or supply-side changes. The effect is concentrated in restaurants where the tourist clientele was from countries that have few social ties with the French population, suggesting that xenophobic tendencies might be at play.

This paper contributes to an emerging literature on the effects of tourism on locals' welfare. While the existing literature emphasizes price channels, i.e. tourists driving up prices (Allen et al., 2020) and endogenous adjustment of amenities (Almagro and Domınguez-Iino, 2019), we show that tourism has an additional effect on existing amenities which lowers their experienced quality.

While we do not aim to evaluate the overall welfare impact of tourism in this paper, we highlight an additional source of discontent that can be caused by tourism. This adds to the debate preceding the pandemic on limiting tourism inflows in some of the most popular tourist destinations. It remains an open question whether tourism will rebound to its pre-pandemic levels. If it does not, our paper provides a preview how persistently lower inflows may affect locals' quality of life.

[14] See section 2.6 for a description of the SCI.

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Figure 1: Daily Number of Reviews in Paris (since launch of Tripadvisor)

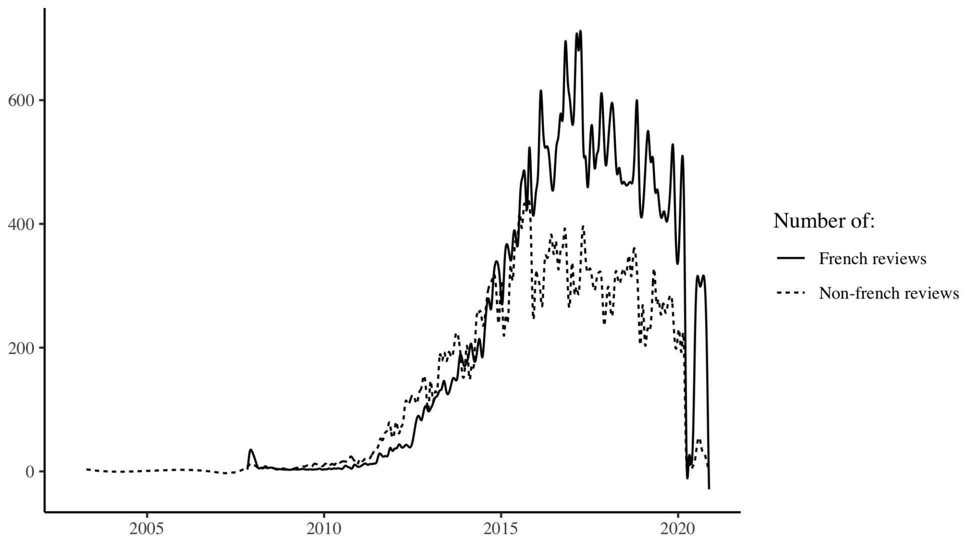

Figure 2: Daily Number of Reviews in Paris

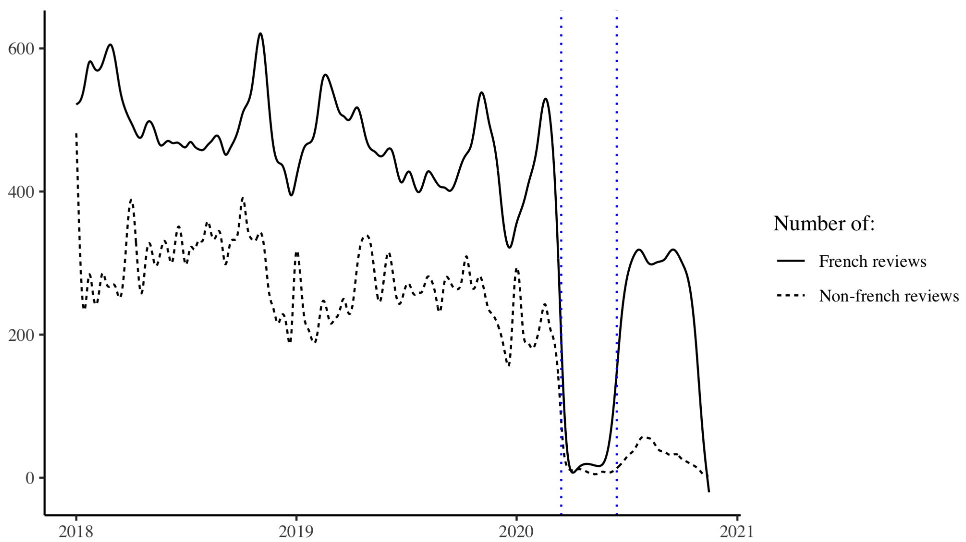

Figure 3: Map of restaurants by share of non-french reviews

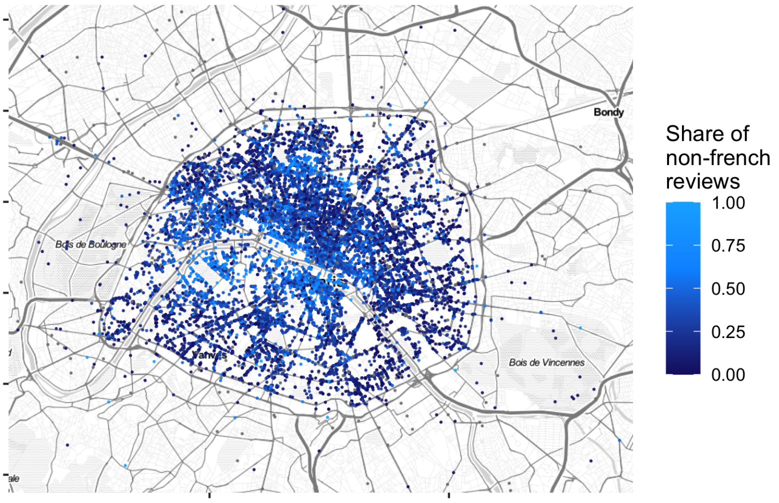

Figure 4: Grid map of restaurants density

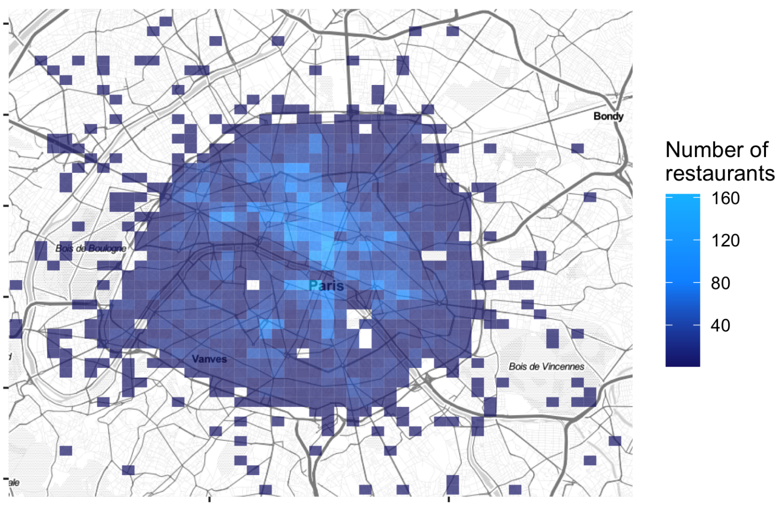

Figure 5: Tourist Access vs Tourism Proxy

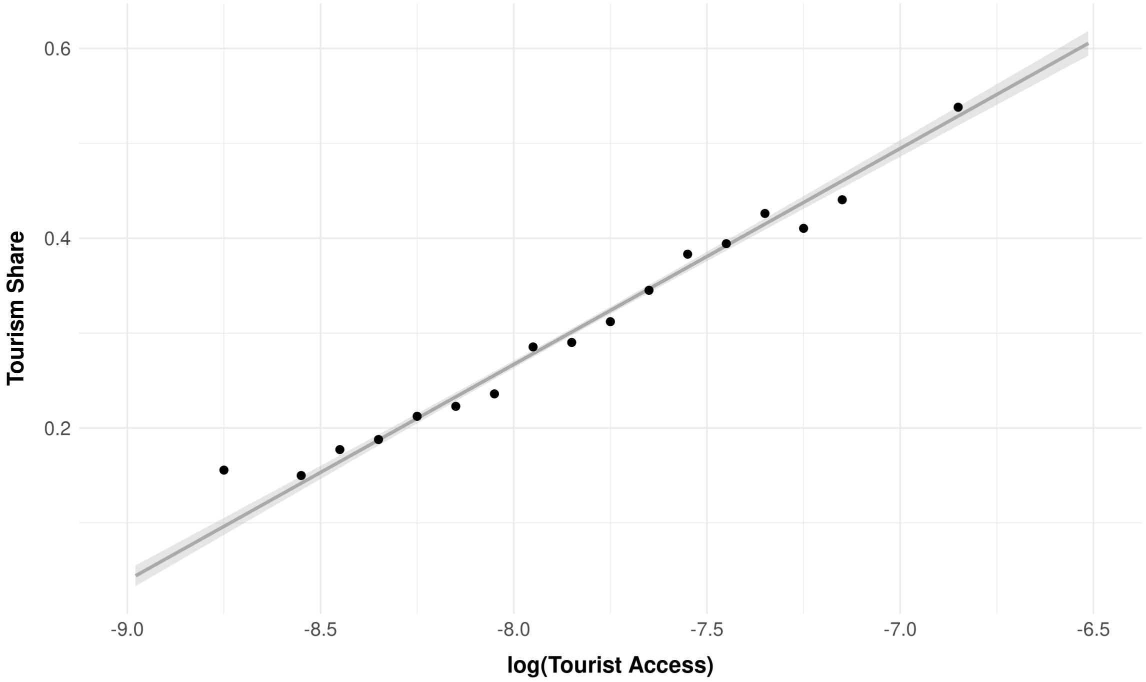

Figure 6: Share of French Cuisine

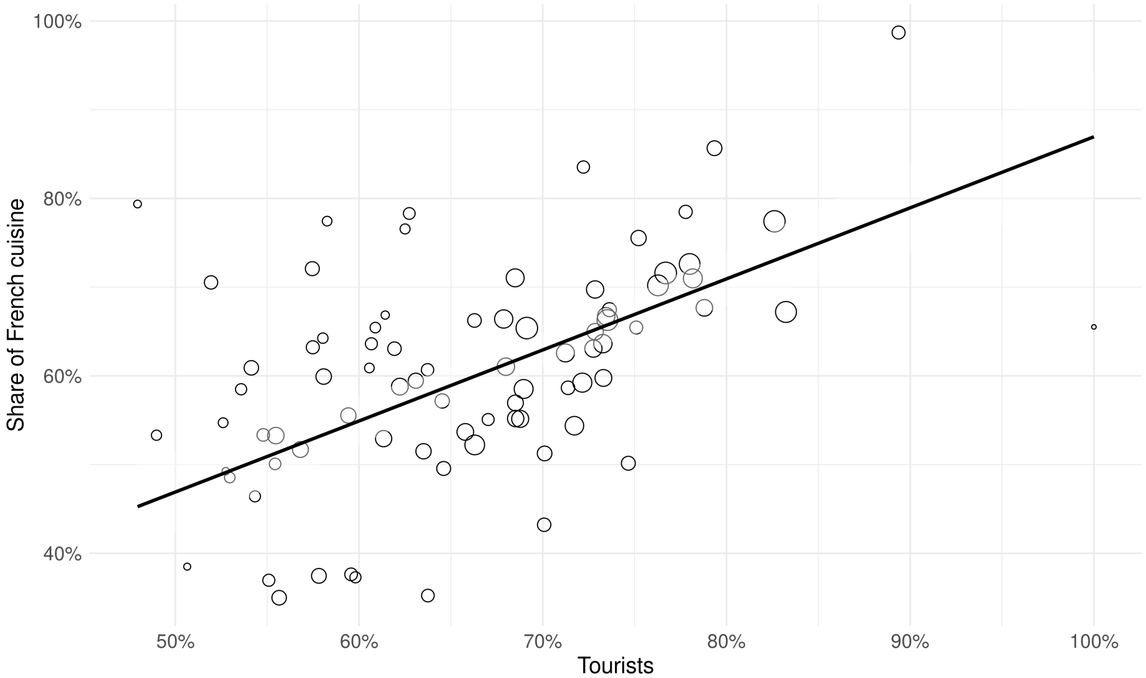

Figure 7: Diversity of Cuisine Types

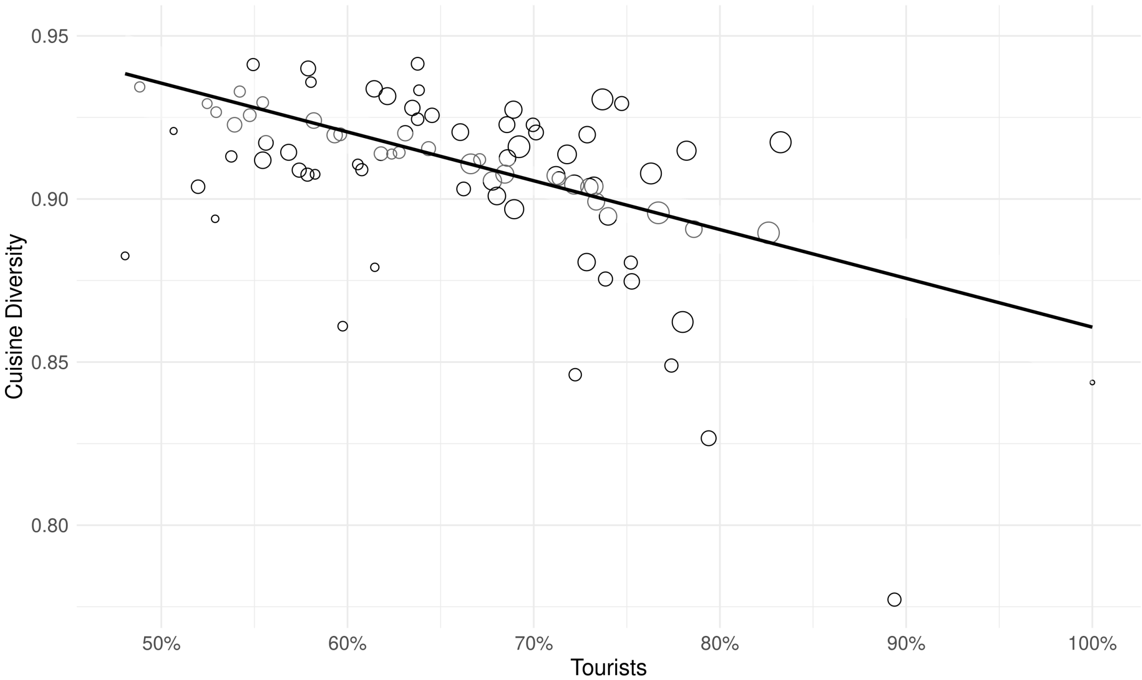

Figure 8: Dynamic Effects

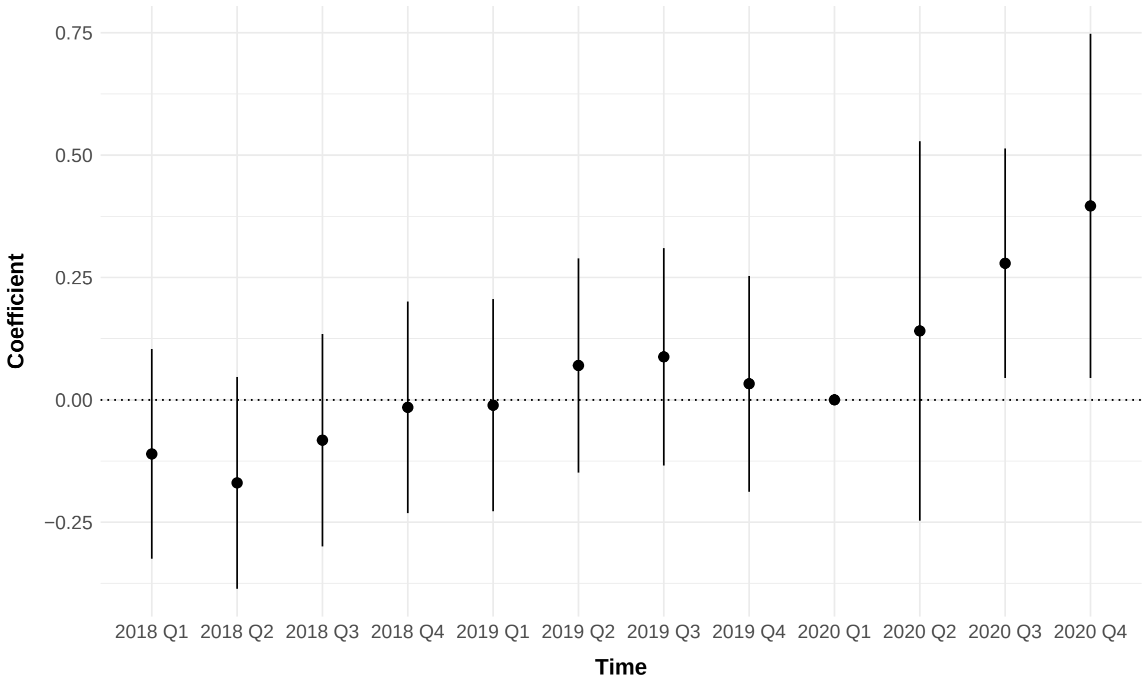

Table 1: Stylized Facts: User Preferences

Dependent Variable:		Rating	
Model:	(1)	(2)	(3)
Variables			
Tourism Share	-0.3932***	-0.2541***	-0.3068***
	(0.0856)	(0.0710)	(0.0700)
log(Num of Reviews)	0.0245*	0.0089	0.0189**
	(0.0130)	(0.0100)	(0.0093)
Fixed-effects			
User		Yes	Yes
Quartier			Yes
Fit statistics			
Observations	109,210	109,210	109,210
R^2	0.00274	0.61455	0.61866
Dependent variable mean	3.8669	3.8669	3.8669

Notes. This table reports OLS estimates. In all columns the unit of analysis is an individual review. Dependent variable is a review's rating. The tourism share is measured as the share of non-French reviews left on a restaurant's page until 2020. Standard-errors clustered at the quarters level are in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 2: Main Result: Tourism and Restaurant Ratings by Parisians (Restaurant-Level)

	Avg. Rating by Parisian			
	(1)	(2)	(3)	(4)
Variables				
Tourism share × Post-Lockdown	0.3008***	0.3244***		
	(0.0789)	(0.0952)		
Top 25% Most Touristic × Post-Lockdown			0.1110***	0.1037**
			(0.0368)	(0.0410)
Fixed-effects				
Restaurant	Yes	Yes	Yes	Yes
Month	Yes		Yes	
Month × Quarter		Yes		Yes
Fit statistics				
Observations	75,876	75,876	75,876	75,876
R^2	0.35637	0.38035	0.35631	0.38029
Dependent variable mean	3.8599	3.8599	3.8599	3.8599

Notes. This table reports OLS estimates. In all columns the unit of analysis is a pair Month × Restaurant. Dependent variable is an average rating of restaurants among users with home location in Paris. The tourism share is measured as the share of non-French reviews left on a restaurant's page until 2020. Post-lockdown is a dummy, which is switched on in June, 2020 – after the first COVID-19 lockdown. Standard-errors clustered at the quarters level are in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 3: Main Result: Tourism and Restaurant Ratings by Parisians (Review-Level)

	Rating			
	(1)	(2)	(3)	(4)
Variables				
Tourism Share × Post-Lockdown	0.2781***	0.1866*	0.2587**	0.3393**
	(0.0830)	(0.0969)	(0.1205)	(0.1558)
Fixed-effects				
Restaurant	Yes	Yes	Yes	Yes
Month	Yes	Yes		
User		Yes	Yes	
Month × Quarter			Yes	Yes
User × Post-Lockdown				Yes
Fit statistics				
Observations	120,314	120,314	120,314	120,314
R^2	0.28145	0.73488	0.74564	0.76153
Dependent variable mean	3.8803	3.8803	3.8803	3.8803

Notes. This table reports OLS estimates. In all columns the unit of analysis is an individual review. The sample consists of reviews left by users with home location in Paris. Dependent variable is a review's rating. The tourism share is measured as the share of non-French reviews left on a restaurant's page until 2020. Post-lockdown is a dummy, which is switched on in June, 2020 – after the first COVID-19 lockdown. Standard-errors clustered at the quarters level are in parentheses.
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 4: Tourism and "Dans Ma Rue" Complaints

	# Complaints			
	(1)	(2)	(3)	(4)
Variables				
Share Tourism × Post-Lockdown	-0.6570***	-0.2581*		
	(0.2272)	(0.1364)		
Top 25% Most Touristic			-0.3527***	-0.1504**
× Post-Lockdown			(0.1213)	(0.0726)
Fixed-effects				
Restaurant	Yes	Yes	Yes	Yes
Month	Yes		Yes	
Month × Quarter		Yes		Yes
Fit statistics				
Observations	366,930	305,332	366,930	305,332
R^2	0.48157	0.68477	0.48024	0.68481
Dependent variable mean	0.40114	0.48207	0.40114	0.48207

Notes. This table reports PPML estimates. The dependent variable is the number of complaints registered on the "Dans ma rue" platform within 100m of a restaurant in a given month. The tourism share is measured as the share of non-French reviews left on a restaurant's page until 2020. Post-lockdown is a dummy, which is switched on in June, 2020 – after the first COVID-19 lockdown. Standard-errors clustered at quartier level are in parentheses.
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 5: Textual Outcomes

	Tourists (1)	Low Food Quality (2)	Too Expensive (3)	Too Noisy (4)	Long Wait (5)
Panel A: restaurant-level					
Variables					
Tourism Share × Post-Lockdown	-0.0646***	-0.0032	0.0044	0.0093	-0.0132
	(0.0112)	(0.0190)	(0.0142)	(0.0109)	(0.0123)
Fixed-effects					
Restaurant	Yes	Yes	Yes	Yes	Yes
Month x Quarters	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	75,997	75,997	75,997	75,997	75,997
R^2	0.24881	0.23065	0.19966	0.18782	0.19802
Dependent variable mean	0.02306	0.07168	0.04727	0.02365	0.02561
Panel B: review-level					
Variables					
Tourism Share × Post-Lockdown	-0.0891***	-0.0032	-0.0334	0.0145	-0.0332
	(0.0222)	(0.0311)	(0.0278)	(0.0265)	(0.0223)
Fixed-effects					
User-Post-Lockdown	Yes	Yes	Yes	Yes	Yes
Restaurant	Yes	Yes	Yes	Yes	Yes
Month × Quarters	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	111,756	111,756	111,756	111,756	111,756
R^2	0.56827	0.60988	0.53738	0.47727	0.53808
Dependent variable mean	0.02274	0.07506	0.05095	0.02816	0.02702

Notes. This table reports OLS estimates. In all columns of Panel A the unit of analysis is a pair restaurant × month. In all columns of Panel B the unit of analysis is an individual review. Dependent variable is constructed from reviews' texts with the help of dictionaries described in Appendix. In panel A dependent variable is a share of reviews related to the corresponding topic (by restaurant-month). In panel B depended variable is a dummy that switch on when a review is related to a topic. The tourism share is measured as the share of non-French reviews left on a restaurant's page until 2020. Post-lockdown is a dummy, which is switched on in June, 2020 – after the first COVID-19 lockdown. Standard-errors clustered at the quarters level are in parentheses.
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 6: Social Proximity

	Avg. Rating by Parisian			
	(1)	(2)	(3)	(4)
Variables				
Tourism Share × Post-Lockdown	0.3073**			
	(0.1206)			
Tourism Share × Post-Lockdown × High SCI		0.1623		
		(0.1506)		
Tourism Share × Post-Lockdown × Low SCI		0.3379***		
		(0.1209)		
Top 25% Most Touristic × Post-Lockdown			0.0865	
			(0.0571)	
Top 25% Most Touristic × Post-Lockdown × High SCI				0.0384
				(0.0674)
Top 25% Most Touristic × Post-Lockdown × Low SCI				0.1209*
				(0.0637)
Fixed-effects				
Restaurant	Yes	Yes	Yes	Yes
Month x Quarter	Yes	Yes	Yes	Yes
Fit statistics				
Observations	62,050	62,050	62,050	62,050
R^2	0.36701	0.36705	0.36696	0.36698
Dependent variable mean	3.8055	3.8055	3.8055	3.8055

Notes. This table reports OLS estimates. In all columns the unit of analysis is a pair Month × Restaurant. Dependent variable is an average rating of restaurants among users with home location in Paris. The tourism share is measured as the share of non-French reviews left on a restaurant's page until 2020. Post-lockdown is a dummy, which is switched on in June, 2020 – after the first COVID-19 lockdown. Measure of network proximity between countries of origin are constructed using Facebook data. Restaurants with different proximity score were divided into two groups: above and below median proximity, High and Low SCI respectively. Standard-errors clustered at the quarters level are in parentheses.
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 7: Textual Outcomes and Social Proximity

	Tourists (1)	Low Food Quality (2)	Too Expensive (3)	Too Noisy (4)	Long Wait (5)
Variables					
Tourism Share	-0.0491***	0.0197	0.0295	0.0043	-0.0162
× Post-Lockdown	(0.0096)	(0.0177)	(0.0334)	(0.0241)	(0.0130)
(0.0153)					
× High SCI					
Tourism Share	-0.0816***	-0.0221	0.0077	0.0171	-0.0135
× Post-Lockdown	(0.0160)	(0.0247)	(0.0183)	(0.0120)	(0.0135)
× Low SCI					
Fixed-effects					
Restaurant	Yes	Yes	Yes	Yes	Yes
Month × Quarter	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	62,079	62,079	62,079	62,079	62,079
R^2	0.24497	0.22017	0.18684	0.18442	0.18753
Dependent variable mean	0.02580	0.07424	0.04878	0.02452	0.02618

Notes. This table reports OLS estimates. In all columns the unit of analysis is a pair Month × Restaurant. Dependent variable is constructed from reviews' texts with the help of dictionaries described in Appendix. It is a share of reviews related to the one of corresponding topics (by restaurant-month). The tourism share is measured as the share of non-French reviews left on a restaurant's page until 2020. Post-lockdown is a dummy, which is switched on in June, 2020 – after the first COVID-19 lockdown. Measure of network proximity between countries of origin are constructed using Facebook data. Restaurants with different proximity score were divided into two groups: above and below median proximity, High and Low SCI respectively. Standard-errors clustered at the quarters level are in parentheses.
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 8: Spillovers

Dependent Variable:	Avg. Rating by Parisian			
Model:	(1)	(2)	(3)	(4)
Variables				
Tourism Share × Post-Lockdown	0.3053***	0.2790***	0.3095***	0.2775***
	(0.0836)	(0.1007)	(0.1020)	(0.1036)
Touristic Area (<100m) × Post-Lockdown		-0.1396		0.0018
		(0.1512)		(0.1551)
Touristic Area (100m-300m) × Post-Lockdown		0.4084*		0.4558*
		(0.2432)		(0.2657)
Touristic Area (300m-500m) × Post-Lockdown		0.0834		0.1179
		(0.2977)		(0.3427)
Touristic Area (500m-1000m) × Post-Lockdown		-0.3662		0.0816
		(0.2911)		(0.4458)
Fixed-effects				
Restaurant	Yes	Yes	Yes	Yes
Month	Yes	Yes		
Month × Quarter			Yes	Yes
Fit statistics				
Observations	63,410	63,410	63,410	63,410
R^2	0.34439	0.34445	0.37327	0.37333
Dependent variable mean	3.8157	3.8157	3.8157	3.8157

Notes. This table reports OLS estimates. In all columns the unit of analysis is a pair Month × Restaurant. Dependent variable is an average rating of restaurants among users with home location in Paris. The tourism share is measured as the share of non-French reviews left on a restaurant's page until 2020. Post-lockdown is a dummy, which is switched on in June, 2020 – after the first COVID-19 lockdown. Standard-errors clustered at the quarters level are in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Part

Appendix

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A Additional Plots

Figure A.1: Tripadvisor interface

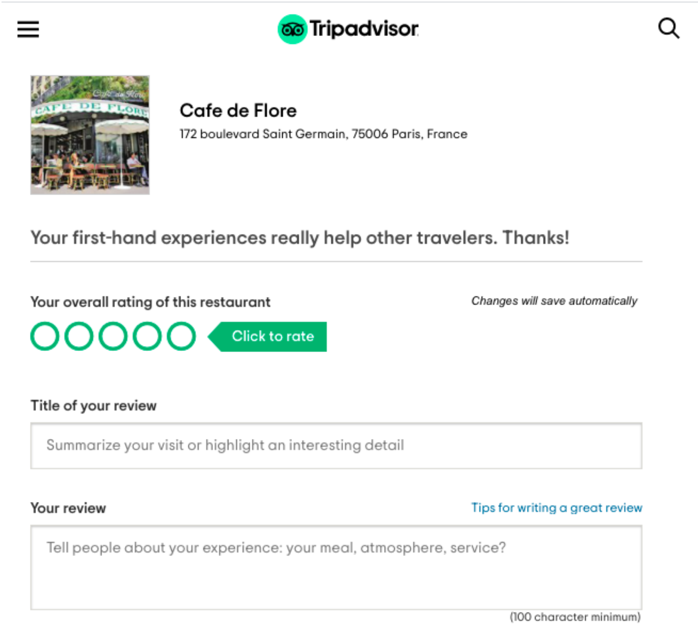
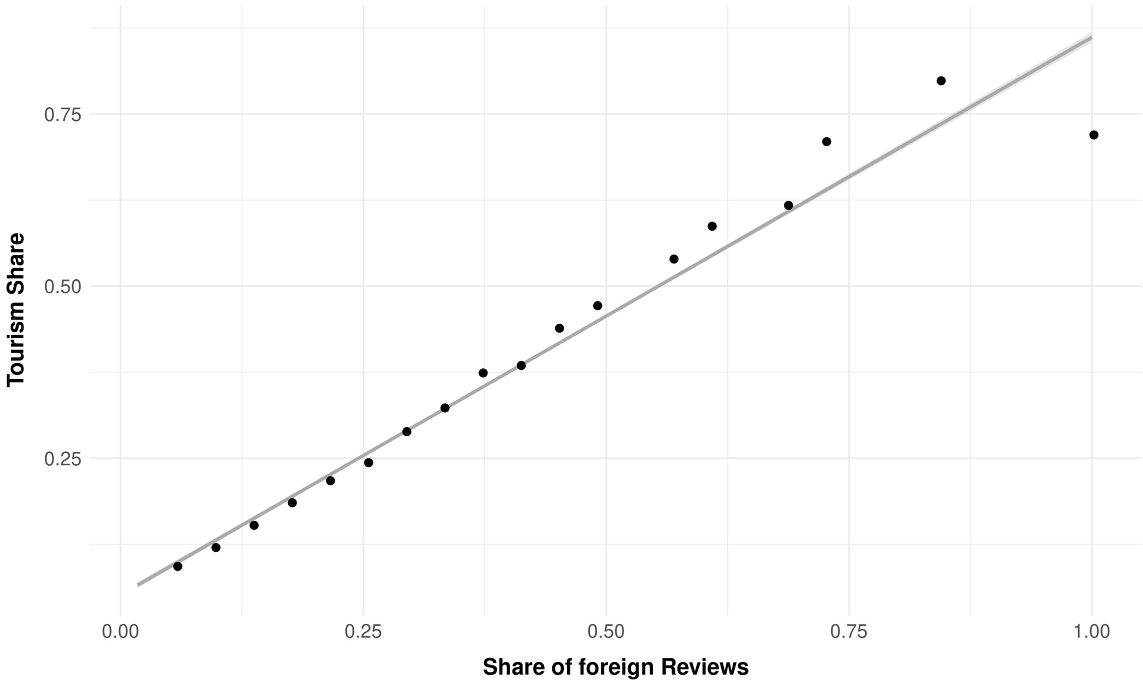


Figure A.2: Correlating Different Tourism Proxies



B Robustness Checks

B.1 Alternative Identification: November 2015 Paris attacks

Table B.1: Tourism and Rating: November 2015 Paris attacks

	Rating by Parisians		Rating by Non-Parisians	
	(1)	(2)	(3)	(4)
Variables				
Tourism Share × Post-Attack	0.0992**	0.1096**	0.0216	0.0248
	(0.0445)	(0.0508)	(0.0264)	(0.0314)
Fixed-effects				
Restaurant	Yes	Yes	Yes	Yes
Month	Yes		Yes	
Month × Quarter		Yes		Yes
Fit statistics				
Observations	44,572	44,572	64,387	64,387
R^2	0.35707	0.37938	0.31664	0.33293
Within R^2	0.00015	0.00015	1.36×10^{-5}	1.36×10^{-5}

One-way (Restaurant) standard-errors in parentheses
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

B.2 Location-Based Tourism Measure

Table B.2: Location-Based Measure: Tourism and Restaurant Ratings by Parisians: Restaurant-Level Analysis

	Avg. Rating by Parisian			
	(1)	(2)	(3)	(4)
Variables				
Tourism Share (location-based) × Post-Lockdown	0.4356***	0.3984***		
	(0.0925)	(0.0985)		
Top 25% Most Touristic (location-based) × Post-Lockdown			0.1569***	0.1438***
			(0.0409)	(0.0442)
Fixed-effects				
Restaurant	Yes	Yes	Yes	Yes
Month	Yes		Yes	
Month x Quarter		Yes		Yes
Fit statistics				
Observations	75,822	75,822	75,822	75,822
R^2	0.35615	0.38011	0.35608	0.38007
Dependent variable mean	3.8595	3.8595	3.8595	3.8595

Clustered (quarter level) standard-errors in parentheses
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table B.3: Location-Based Measure: Tourism and Restaurant Ratings by Parisians: Review-Level Analysis

	Rating			
	(1)	(2)	(3)	(4)
Variables				
Share Tourism (location-based) × Post-Lockdown	0.4290***	0.3172***	0.3592***	0.3868***
	(0.0983)	(0.1156)	(0.1288)	(0.1430)
Fixed-effects				
Restaurant	Yes	Yes	Yes	Yes
Month	Yes	Yes		
User		Yes	Yes	
Month × Quarters			Yes	Yes
User × Post-Lockdown				Yes
Fit statistics				
Observations	120,252	120,252	120,252	120,252
R^2	0.28131	0.73480	0.74557	0.76145
Dependent variable mean	3.8800	3.8800	3.8800	3.8800

Clustered (quarter-level) standard-errors in parentheses
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table B.4: Location-Based Measure: Textual Outcomes

	Tourists (1)	Low Food Quality (2)	Too Expensive (3)	Too Noisy (4)	Long Wait (5)
Variables					
Tourism Share	-0.0562***	-0.0213	0.0013	-0.0014	-0.0165
(location-based)	(0.0111)	(0.0186)	(0.0155)	(0.0109)	(0.0119)
$\times$ Post-Lockdown					
Fixed-effects					
Restaurant	Yes	Yes	Yes	Yes	Yes
Month $\times$ Quarter	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	75,943	75,943	75,943	75,943	75,943
R^2	0.24864	0.23044	0.19964	0.18781	0.19802
Dependent variable mean	0.02308	0.07171	0.04730	0.02367	0.02563

Clustered (quarter-level) standard-errors in parentheses
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

B.3 Aggregation of Language-Based Tourism Measure by Different Periods

Table B.5: Tourism and Ratings: Language-Based Tourism Aggregated by Different Periods

	Avg. Rating by Parisian				
	(1)	(2)	(3)	(4)	(5)
Variables					
Tourism share (before 2017) × Post-Lockdown	0.2659**				
	(0.1114)				
Tourism share (before 2018) × Post-Lockdown		0.3171***			
		(0.1082)			
Tourism share (before 2019) × Post-Lockdown			0.3451***		
			(0.0987)		
Tourism share (before 2020) × Post-Lockdown				0.3244***	
				(0.1016)	
Tourism share (before 2021) × Post-Lockdown					0.3290***
					(0.1095)
Fixed-effects					
Restaurant	Yes	Yes	Yes	Yes	Yes
Month x Quarter	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	57,292	65,515	72,112	75,876	76,350
R^2	0.37559	0.37228	0.37469	0.38035	0.38273
Dependent variable mean	3.7902	3.8156	3.8433	3.8599	3.8626

Clustered (quarter-level) standard-errors in parentheses
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

B.4 Clustering

Table B.6: Tourism and Ratings: Different Clustering

	Avg. Rating by Parisian			
	(1)	(2)	(3)	(4)
Variables				
Tourism Share × Post-Lockdown	0.3244***	0.3244***	0.3257***	0.3257***
	(0.1016)	(0.0979)	(0.0952)	(0.0952)
Fixed-effects				
Restaurant	Yes	Yes	Yes	Yes
Month × Quarter	Yes	Yes	Yes	Yes
Clustering				
	Quarter	Grid cell	Restaurant	No
Fit statistics				
Observations	75,876	75,884	75,961	75,961
R^2	0.38035	0.38046	0.38098	0.38098
Dependent variable mean	3.8599	3.8598	3.8592	3.8592

Clustered (quarter-level) standard-errors in parentheses
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

C Validation of Tourism Measures

Table C.1: Tourist Access

	Tourism Share			
	(1)	(2)	(3)	(4)
Variables				
log(Tourist Access)	0.2443***	0.2170***	0.2450***	0.1409***
	(0.0171)	(0.0369)	(0.0215)	(0.0326)
Weighted			Yes	Yes
Fixed-effects				
Quartier		Yes		Yes
Fit statistics				
Observations	10,179	10,179	10,179	10,179
R^2	0.22746	0.31021	0.26590	0.39319
Dependent variable mean	0.31451	0.31451	0.31451	0.31451

Clustered (quarter-level) standard-errors in parentheses
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

D Text Analysis

Table D.1: Dictionary for Text Analysis

Low Food quality			
pas bon	sans goût	aucun saveur	réchauff
pas très bon	aucun goût	fade	cuisine bof
mauvaise cuisson	goût bizzare	industriel	avarié
pas assez cuit	trop cuit	supermarch	tombé malade
pas cuit	sans saveur	mauvaise qualité	vomir
indigestion	intoxication	pas frais	surgel
insipid	dégueulass	degueulass	micro-ond
pas fait maison			
Too Expensive			
prix élevés	cher	prix sont élevés	prix sont très élevés
Too Noisy			
bruyant	beaucoup de bruit		
Long Wait			
long	lent		
Tourism			
touris			

Notes. This table reports phrases that were used in our text analysis. Terms are not always the full forms of the words, which helps to take into account the syntax. We also do not include to this table potential distortions of the same phrases, which were also used in our analysis (missing accent marks, common misspellings).

Table D.2: Summary Statistics for Textual Variables

Variable	N	Mean	St. Dev.
Tourism	1,154,860	0.025	0.157
Low Food Quality	1,154,860	0.066	0.248
Too Expensive	1,154,860	0.050	0.218
Too Noisy	1,154,860	0.028	0.165
Long Wait	1,154,860	0.024	0.153

Table D.3: Ratings and Textual Variables

	Rating					
	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Tourists	-0.3413***					-0.2868***
	(0.0370)					(0.0363)
Low Food Quality		-1.163***				-1.138***
		(0.0208)				(0.0207)
Too Expensive			-0.4439***			-0.3939***
			(0.0228)			(0.0214)
Too Noisy				-0.2186***		-0.1930***
				(0.0275)		(0.0255)
Long Wait					-0.4257***	-0.3845***
					(0.0280)	(0.0255)
Fixed-effects						
User	Yes	Yes	Yes	Yes	Yes	Yes
Restaurant	Yes	Yes	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	112,905	112,905	112,905	112,905	112,905	112,905
R^2	0.74586	0.76787	0.74789	0.74560	0.74653	0.77195
Dependent variable mean	3.8863	3.8863	3.8863	3.8863	3.8863	3.8863

Clustered (quarter-level) standard-errors in parentheses
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1