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The Rise and Fall of Short-term Rentals: Using App Data to Evaluate the Impact of COVID-19 on Local Economic Activity

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Abstract

We study the causal impact of COVID-19's negative shock on short-term rentals in Lisbon's local economy. Our difference-in-differences strategy uses a treatment relying on the pre-pandemic short-term rentals intensity, at the parish level, using unexploited app data, between 2018Q3 and 2020Q3. The number of likes and comments measure the economic activity level. The results suggest that likes and comments fell by 48.6% and 56.1%, for Cafés, and by 69.6% and 56.1%, for Pastries. Likes and comments fell in restaurants of treated areas *vis-à-vis* in comparison areas. Our results are robust to including Porto and other exercises restricting the sample period.

Keywords: Economics, Public Policy, Short-term rentals, Restaurants, Amenities

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1 Introduction

Tourism activities have grown tremendously in the last few years. Exception made to the recent COVID-19 pandemic years, the tendencies have been of significant growth from one year to another (WTO 2020). As a consequence, accommodation demand and supply took different shapes and forms. Hotels and related accommodation supply were not only not enough to meet the high demand, but they also no longer filled out all the tourists' requirements. The desire for a *local* experience makes visitors rely on peer-to-peer platforms, choosing residencies owned by local property owners. In Lisbon, the phenomenon has been especially intense; indeed, in 2019, the Portuguese capital was the European city with the highest ratio between number of houses on Airbnb per inhabitant[1]. This shows a clear penetration of the online platform into the city - and, more particularly, in its real estate market.

As the residential demographics change, the business landscape might undergo some adjustments as well, since it is a function of local demand (Waldfogel 2008). Individuals are more likely to consume around their residence (Hidalgo et al. 2022), particularly visitors, who do not have access to a car or are unfamiliar with the public transportation system. Thus, amenities in higher short-term rental densities areas may differ from lower density ones, in both quality and quantity terms (Kuang 2017), and affect the local economy of each region differently (Basuroy et al. 2020 and Schiff 2015). Although food establishments are not the only amenity searched for and desired by tourists, in this paper, we will use it as a proxy to measure the change in the business landscape of the city, as it is a good representation of the facilities and conveniences the city provides (Glaeser et al. 2018).

The goal of this paper is to study the effect of short-term rentals on the amenities of the city. We do so by exploiting the outbreak of the COVID-19 pandemic, comparing civil parishes with a higher density of short-term rentals with the remaining ones. We assign civil parishes to the treatment group when they contain neighbourhoods that are

[1] See https://www.onlinemarketplaces.com/articles/lisbon-has-highest-ratio-of-airbnb-locations-in-europe/

subject to the bans on short-term rental registries implemented in Lisbon in 2018 and 2019.[2] Overall, we look at the impact of the pandemic in the local economic activity of Lisbon, keeping in mind that restaurants are a key part of that and hence used as a proxy for the amenities supply (Leonardi and Moretti 2022). To measure that supply, we use data from Zomato, a peer-to-peer platform, which provides information (e.g., menus, prices, user-reviews) of restaurants in selected cities. The platform is of particular interest in Lisbon because it is one of the country's regions where it is widely spread, detaining the majority of the App and website traffic[3].

Given the consistent penetration of both platforms into the city, Lisbon is a great lab to study how a sudden stop in short-term rentals demand affects the overall amenities of the city, measured by Zomato's data. Besides, the pandemic was a quite unique shock that affected the peer-to-peer platforms (Femenia-Serra et al. 2022) (as well as the city as a whole) and changed the course of the growth trend in terms of both tourism and amenities supply (Llaneza Hesse and Raya Vılchez 2022). This abrupt stop was particularly noticeable in economies that rely a lot on tourism, such as Lisbon's.

We combine publicly available web-scraped data on short-term rentals listings in Lisbon with high-quality data on Zomato's platforms (App and Website). Our unit of observation is the restaurant, for which we have individual data on Average Ratings, Likes, and Comments. We also aggregate at the civil parish level to analyse the number of restaurants. The parishes in our treatment and control groups are similar in terms of residents' socioeconomic characteristics and population density. Most importantly, they are geographically close within the city borders, so it is unlikely to see individuals move from one of these parishes to another due to innate characteristics of these areas, such as space or commuting costs. Thus, the parishes differ, on average, at the short-term properties intensity level and in regards to restaurants' supply.

In our empirical analysis, the dependent variables are the *i)* number of restaurants in the city, *ii)* average ratings of each restaurant, *iii)* number of likes each restaurant

[2]This includes seven civil parishes in Lisbon: Avenidas Novas, Arroios, Estrela, Misericórdia, Santa Maria Maior, Santo António, and São Vicente. The remaining are assigned to the control group.

[3]See https://medium.com/zomatoblogportugal/zomato-em-portugal-a-hist%C3%B3ria-contada-por-miguel-ribeiro-86925735f3e3

was given, and *iv)* number of comments written about each restaurant. We combine data on these variables of interest, to analyze the impact of the pandemic, considering parishes with high and low density levels of short-term rentals. Next, we implement a difference-in-differences design with a binary treatment specification that uses the civil parishes targeted by the partial bans on new short-term rental licences implemented by the municipality of Lisbon in 2018 and 2019 as the treated units. We complement this analysis with a continuous treatment intensity.

Since short-term rentals have grown mostly in central parts of the city, our main identification concern is that parishes that experienced higher short-term rental penetration might simultaneously be experiencing processes of business landscape transformation. To account for potential confounding effects, we control for civil-parish and time fixed effects at the parish level, all time-invariant, so that unobserved characteristics are captured and they do not drive our results.

Our results are as follows: after the outbreak of the pandemic, the number of likes and comments of Zomato's App and website fell significantly. These are indicators of demand, barometers of interaction between the consumers and the online peer-to-peer platform. For Cafés and Pastries, likes and comments fell considerably, reaching magnitudes as large as 69%, for likes, and 56%, for comments. The number of restaurants remained sensibly the same, but some saw their quality ratings decrease.

Our paper contributes to the literature by exploiting a regulatory reform to obtain the causal impact of short-term rentals in the city's local economic activity and amenities. To the best of our knowledge, the usage of Zomato's data, as a proxy to measure those changes in the amenities of the city, has not been done yet. In particular, the case of Lisbon is still to be uncovered.

This paper is organized as follows: Section 2 reviews the existing literature on the effects of peer-to-peer markets on the city's economy; section 3 presents a brief institutional background; section 4 discusses the empirical strategy; section 5 presents the results and includes some robustness checks; finally, Section 6 concludes.

2 Literature Review

Short-term rentals, such as couchsurfing and other blended-living situations, have been widely associated with tourism booms and rearrangements in cities all around the globe, including cosmopolitan European capitals, such as Lisbon. The relationship between these living arrangements and the housing market is well-established, in terms of both supply and demand - and, consequently, prices. For example, an analysis by Garcia-López et al. 2020, focused on Barcelona, concluded that short-term rental platforms (such as Airbnb, for instance) have a substantial impact on neighbourhoods, increasing both rents and overall prices.

Although somewhat of a recent topic, the literature on the effect of peer-to-peer online platforms on the city's backbone is growing quite rapidly. Several studies have focused on the subject, in European cities (Gonçalves et al. 2020), as well as North-American (Koster et al. 2021). The vast extent of the literature focuses on the housing market of the cities. For example, Sheppard et al. 2016; Barron et al. 2018; as well as Franco and Santos 2021 conclude that the presence of Airbnb leads to an increase in either rents or prices (or both). Guttentag 2015 even suggest the creation of an informal tourism accommodation sector, raising legality and tax concerns. Furthermore, Amore et al. 2020 studied the impact of short-term rentals on other European cities, in countries with similar economic features: Lisbon, Portugal; Milan, Italy; and Athens, Greece. The study looked at rents and overall prices - and demonstrated that both increased in the presence of these short-term rental platforms. Particularly, in Lisbon, properties in key tourist areas are currently valued well above the average house price of the country. According to Amore et al. 2020, increases of 43% and 52.4% have been registered in Baixa and Avenida da Liberdade, respectively.

The reviews from Wachsmuth and Weisler 2018, as well as Jiao and Bai 2020, confirm that the impact of such platforms goes way beyond the financial and economical spectrum. Both papers cover quite important geographic distributional points and show that these platforms are stronger than what is believed, as they have the ability to redesign, reshape, and reorganize cities as a whole. For example, Jiao and Bai 2020 show that Airbnb listings were heavily concentrated in Manhattan, in New York City, and more evenly distributed in Los Angeles. This can then have an impact on the policies implemented to specific parts of the city.

This paper is also related to the literature on the exposure of the online platforms to the pandemic outbreak. Ferreira et al. 2022 argue that the lockdown decelerated our day-to-day life, but it also potentiated a tremendous acceleration of the platformization of the economic activity. The authors conclude that the pandemic came to highlight the power and relevance of these peer-to-peer online apps/websites. Batalha et al. 2022 makes use of these powerful online tools and concludes that COVID-19 was responsible for a fall of over 4% in house prices, in Lisbon.

Note, however, how the majority of the aforementioned papers fails to account for city-life changes, including the restaurants' supply of a municipality, for example. Glaeser et al. 2018 gets close to it by exploring Yelp's data in New York city to evaluate both local housing prices and neighbourhood changes, via several numerical variables (e.g., number of groceries and restaurants).

3 Institutional Background

According to Statistics Portugal, in August 2019, over three million people visited Portugal, 832,926 of which chose Lisbon as their destination[4]. On the same month, over two million overnight stays were registered in the capital. The local economy followed the positive growth trends of tourism. More accommodations were being provided to the increasing number of visitors. By the same token, amenities and available services in the city were rising.

In 2018, due to concerns over housing affordability, the municipality of Lisbon restricted new registries in areas with a short-term rentals to total property ratio above 25%, the so-called *Zonas Turísticas Homogéneas*, which were then updated in 2019 to include additional neighbourhoods (Proposal 204/CM/2019). In 2019, Porto's municipality approved a similar legislation, encompassing two civil parishes. We exploit these legislative changes in the identification strategy (Edital NUD/260310/2019/CMP).

[4]This is measured in number of guests in tourist accommodation establishments

On March 2nd, 2020, Portugal registered its first COVID-19 case[5]. Ten days later, the Prime Minister announces the closing of clubs, as well as the reduction of the number of people allowed in restaurants, malls, and public services. On the 14th, bars are forced to close before 9pm. On the 19th, State of Emergency is declared: mandatory curfew for everyone and high restrictions on the circulation of people, including tourists. In fact, even before it was mandatory, according to Google mobility data, people considerably decreased their visits to restaurants eight days before the official imposition by the government (Carvalho et al. 2021). This comes to show that individual choice and one's own fear of infection played, too, an important role during the lockdown period (Goolsbee and Syverson 2021, decreasing demand considerably. Hotels, restaurants, shops, theaters closed down with no perspectives of reopening - and some never did.

By the end of April, restaurants were given a new prospect: reopening will be possible on the 18th of May. On the 16th, there is an incentive by the government for people to revisit restaurants, although with caution (e.g., mandatory mask use and disinfection of hands). By the end of May, the restaurants were back to their normal capacity, as long as physical distances were complied and acrylics were used to separate customers. Special rules were applied to Lisbon, given the higher number of cases in the city, in comparison with the rest of the country[6]. At the beginning of November, with another increase of cases, new regulations were imposed: restaurants had to close at 1pm on the weekends. With holidays approaching, many restaurant-owners saw their establishments face even more restrictions.

The density of food establishments in Lisbon is not homogeneous within the city boundaries, as observable in Figure 12, in the Appendix. However, the above-mentioned government rules were applied at the city level, affecting them all.

The impact of the pandemic on the amenities of the city, including the restaurants' sector, is undeniable, mainly during the period in which businesses were not allowed to open. However, even when the food establishments were indeed open, it not always meant

[5]See https://www.tsf.pt/portugal/sociedade/confirmados-dois-primeiros-casos-de-contagio-pelo-novo-coronavirus-em-portugal-11876592.html

[6]See https://www.antenalivre.pt/covid-19/covid-19-dois-anos-principais-acontecimentos-da-pandemia-em-portugal

profit. Uncertainty, distrust, and at times bewilderment towards the imposed rules also determined whether people sought going out or not.

The government implemented measures of financial relief to mitigate the economic fallout. The labour market was significantly impacted, with both an increase in unemployment and a considerable decrease in new job placements (Nunes et al. 2022). Amongst the measures was the layoff method, which translates into either a suspension or a reduction of labour contracts due to profound changes in the markets, while Social Security covered two-thirds of the wage. All in all, this was an attempt to keep the job openings, avoiding massive cutbacks and unemployment rises, until the labour market stabilizes again. Besides, 580 million euros were made available in credit lines for companies of the restaurant sector. Both the layoffs and the credit lines delayed some impacts of the crisis, but it certainly falls short on what is yet to be done.[7] According to Carvalho et al. 2021, the *Specialized Retail and Services* sector, which includes restaurants, experienced the largest drops in the value of transactions during the pandemic period.

4 Empirical Strategy

In this section, we present the data sources used in the paper. Then, we discuss the methodology and compute key descriptive statistics.

4.1 Data Sources

Our paper exploits two sources of data; one on short-term rentals registries and another on the supply of restaurants, as an indicator of the amenities offered in Lisbon. Our units of analysis are both the restaurants and the civil parish. The parishes are quite small units, with an average surface of 4.2 square kilometers across the 24 civil parishes of the city, with an average population of 22,746[8] inhabitants.

[7]Later on, in 2021, other policies were implemented, such as the *iVaucher* initiative (consumers could retain up to 50% of their expenses on certain goods/services, including restaurants, as long as they had asked for their fiscal number on the receipts in the three months prior). Plus, over 200 million euros were provided via *Apoiar.pt*, where restaurant-owners could present their revenue breaks and apply for financial support. These measures were, however, not anticipated by agents during our sample period.

[8]This is the total population of the municipality of Lisbon, in 2021, divided by the 24 civil parishes.

To measure short-term rentals activity, we analyze a publicly available data set from the National Short-Term Rental Registry (RNAL). We collect daily new registries, between the third quarter of 2018 and the third quarter of 2020. Our data includes the universe of legal short-term rentals registered in this period, for which we observe the registry date, address, number of rooms, nationality of the owner, and whether the owner is an individual or a firm.

In order to compute a measure of density (i.e., the share of short term rental), we follow Batalha et al. 2022 procedure: we estimate the total number of dwellings per civil parish and update the number of dwellings available in the 2011 Census, with yearly figures of construction and demolition of buildings in each civil parish, extracted from Statistics Portugal. We also deal with the 2013 reorganization of civil parishes, which, through mergers and splits, transformed the city into its current map of 24 parishes. With the merged civil parishes, we simply add the dwellings.

For the amenities piece, we use Zomato's data set[9], since restaurants' supply is used as a proxy for the business landscape of the city. The data frame includes information from the third quarter of 2018 up until the third quarter of 2020 (the same time frame of the short-term rentals). Zomato's data set includes the ID of the establishment as well as its name, address, type, date of opening and closing, and average rating. In terms of the outcome variables, we use the number of restaurants (aggregated at the civil parish level), amount of comments, and number of likes[10] a food establishment was given were also provided. We recognize that Zomato might not represent 100% of the restaurant supply of the city. However, with over 9,000 entries (roughly, 750 per quarter) for Lisbon only, the numbers are not far from reality[11]. In fact, Zomato has mechanisms in place to have the vast majority of restaurants in the city registered in its platform; indeed, Zomato updates its platform every six months, cleaning any inactive establishments, for instance. Thus, we believe that Zomato's data is a good indicator of the city's supply when it comes to food establishments.

[9]This is provided directly from a contract with Zomato Portugal.

[10]In the data set, comments and likes are named *opinions* and *votes*, respectively.

[11]According to Statistics Portugal, in 2020, the food-related market of establishments with "relevant size" involved 1,116 commercial units, in the Great Lisbon Area.

4.2 Methodology

The goal of our paper is to evaluate if amenities in civil parishes with a higher density of short-term rental properties are more or less affected by the pandemic than lower density ones. Given the geographic proximity of the comparison areas and the similar urban density, it is credible that treatment and comparison civil parishes constitute good counterfactuals of each other, which provides a solid baseline to apply our empirical strategy.

We exploit a difference-in-differences approach based on the exposure of each civil parish to short-term rentals to evaluate four outcome variables of interest per quarter: *i)* quantity of restaurants, *ii)* quality (measured through the average ratings), *iii)* votes (similar to likes), and *iv)* opinions (similar to comments). We look at the number of likes and comments to evaluate the interaction level of the customers with the restaurants. These are much more sensitive in a short period and in an online (App/Website) context.

Our baseline regressions only include civil parishes in Lisbon. However, we also add Porto's for robustness. Two treatment definitions are used: *i)* one that assigns all the civil parishes that contain neighbourhoods covered by the 2018 and 2019 Lisbon bans on new short-term rental licences to the treatment group and *ii)* a continuous treatment alternative, where the treatment intensity is the ratio of short-term rentals to total property in each civil parish in the last quarter of 2019. For simplification purposes, hereinafter, the two treatments will be referred to as *binary* and *continuous*, respectively.

Note that Figure 11 displays a sharp drop in the number of tourists in March, which also is the onset of the pandemic in Portugal. Therefore, the treatment period begins in the first quarter of 2020 (2020Q1). The omitted quarter is the one immediately before: 2019Q4. Since the first quarter of 2020 includes both treated and untreated months, as a robustness check, we exclude 2020Q1 from the analysis, which can be found in the subsection 5.2.

To construct the difference-in-differences estimator, for the binary treatment approach, the treated civil parishes are the *high short-term rental density* ones and the comparison civil parishes are *low short-term rental density*, following Batalha et al. 2022. We assign civil parishes to the treatment group when they contain neighbourhoods that are subject to the bans on short-term rental registries implemented in Lisbon in 2018 and 2019. Since these restrictions were imposed at a smaller geographical scale than that of the civil parish as a whole (Gonçalves et al. 2020), we assume that a civil parish is treated if it contains at least one restricted area. Overall, this includes seven civil parishes in Lisbon: Avenidas Novas, Arroios, Estrela, Misericórdia, Santa Maria Maior, Santo António, and São Vicente, as visible below, in Figure 2. For Porto, two more are added to this list: Bonfim as well as Cedofeita, Santo Ildefonso, Sé, Miragaia, São Nicolau e Vitória (UF Centro Histórico do Porto)[12]. As for the continuous, the treatment intensity is the density of short-term rentals in the last quarter of 2019.

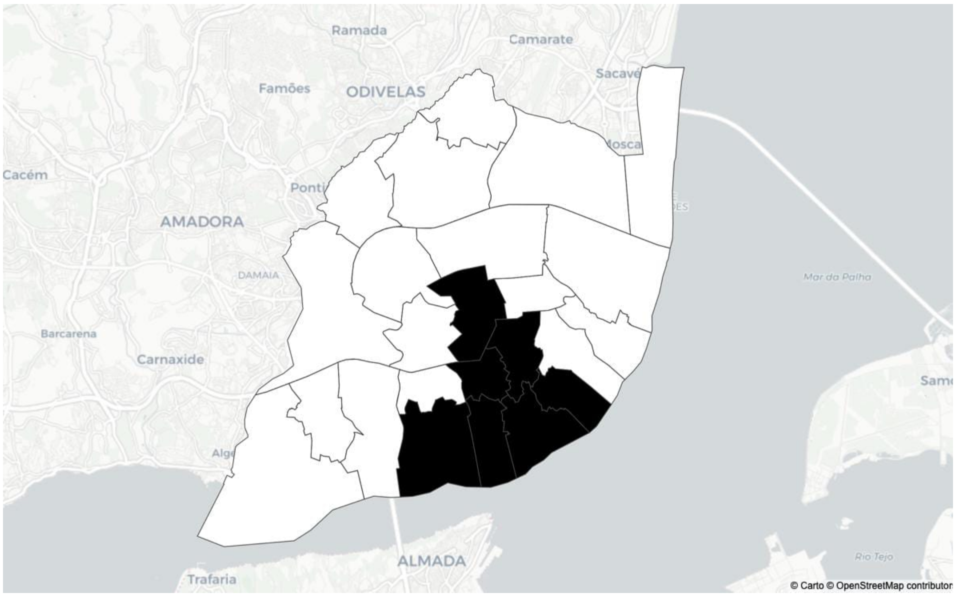


Figure 1: Map of the 24 Lisbon parishes, where the seven treated are in black.

This identification method requires two key assumptions for causal inference: *i)* the absence of contemporary events that might have differently affected civil parishes with higher short-term rental density, as well as *ii)* parallel trends in the outcome variables of interest before treatment. The first is guaranteed by the dimension of the pandemic outbreak. Although COVID-19's impact was not the same across the globe, any other contemporaneous happenings would have little to no energy to compete with such a severe

[12]See Figure 13, in the Appendix

event as the SARS-CoV-2 virus. During several months after the pandemic outbreak, the municipal and the central governments have been concerned about diminishing the effects of the pandemic. Thus, there were no major urban/zoning policies implemented during this period, which could have impacted civil parishes differently. Plus, as aforementioned, the treated and control areas in our study are all high density parishes within the city boundaries, and hence similar to begin with. Additionally, quarter and civil parishes fixed effects are included in the regressions, capturing any time-invariant, unobserved characteristics that could differ during this period.

As for the second assumption needed for our identification strategy, we perform a formal test of the parallel trends. Recall that the treatment period starts in the first quarter of 2020, so the omitted quarter is the one immediately before. We carry out event-study exercises to verify that, before the pandemic, the outcome variables followed parallel trends in the treated and control areas. The test is performed using the following specification for civil parish p and quarter q, for both binary and continuous treatments:

$$y_{pq} = \alpha_p \times \tau_p + \rho_q \times \tau_q + \sum_{2018Q3 \leq q \leq 2019Q3} \delta_q \times Density_p \times \tau_q + \sum_{2020Q1 \leq q \leq 2020Q3} \delta_q \times Density_p \times \tau_q + \epsilon_{pq} \tag{1}$$

where y_{pq} is the outcome variable for civil parish p in quarter q, α_p and λ_q are civil parishes and quarter fixed effects, τ_p and τ_q are indicator variables of civil parish and quarter, and ϵ_{pq} is the error term. Finally, $density_p$ is the treatment indicator (i.e., for the binary case, it is equal to 1 for the civil parishes that contain areas that were covered by the bans on new short-term rental registries by the municipality of Lisbon; and for the continuous one, it takes the value of the ratio of short-term rentals to total property in each civil parish in the last quarter of 2019).

Our baseline difference-in-differences specification is given by:

$$y_{pq} = \alpha_p \times \tau_p + \rho_q \times \tau_q + \beta Post_q \times Density_p + \epsilon_{pq} \tag{2}$$

where all variables are defined as in Equation 1 and $Post_q$ is 1 in the treatment period (starting in the first quarter of 2020). The coefficient of interest, β, for the binary specification, measures the differential impact of the pandemic on high versus low density areas, where high density areas are defined by the bans on short-term rentals implemented by the municipality of Lisbon. The control group of civil parishes that do not include areas covered by the bans is not expected to suffer the effects of the pandemic on the amenities of the city. For the continuous treatment, β measures the causal impact of the pandemic when the intensity of treatment with short-term rental intensity increases by one per 100 dwellings.

The same regression is run four times, one for each of the different food establishments: *i)* Dining (includes Casual Dining, Fine Dining, and Food Courts); *ii)* Bars (includes Bars, Cocktail Bars, Pubs, and Wine Bars); *iii)* Cafés (includes Cafés, Snack Bars, and Quick Bites); and *iv)* Pastries (includes Pastry Shops and Tea Rooms).

Note that, for three out of the four variables of interest (i.e., number of restaurants, likes, and comments), inverse hyperbolic sines are used to ensure proper distribution of the dependent variable. These work similarly to logarithms, but have the add-on of allowing the retention of zero-valued (and even negative-valued) observations (Bellemare and Wichman 2020). Standard errors are robust to account for heteroskedasticity.

4.3 Descriptive Statistics

Before proceeding to the regression results, the trends for the outcome variables are presented below, in Figure 2, for the binary treatment. On the first graph, regarding the number of restaurants, there appears to be no change throughout the period under analysis. In regards to quality (i.e., average ratings), the figure simply presents a tenuous break, suggesting that the variable only suffers a growth slowdown. Given the short-run period analyzed, it is credible to state that the restaurants did not see their ratings decrease due to being closed to the public most of the time. As their doors were closed, the ability to rate them was reasonably limited. Regarding both likes and comments, the rupture of the growth trend is more evident: the quarter after the beginning of the pandemic (2020Q2) presents a fall for both variables of interest. These are indicators of demand, barometers of interaction between the consumers and the online platform. The decrease registered during that period indicates that customers were unable to meet their needs when it came to restaurants.

Note that average prices per meal, although available on our data set, are not used. This is because both the App and the website of Zomato do not create new entries upon changes in prices, unless other modifications are done at the same time, such as the name of the food establishment or the type of cuisine, for instance.

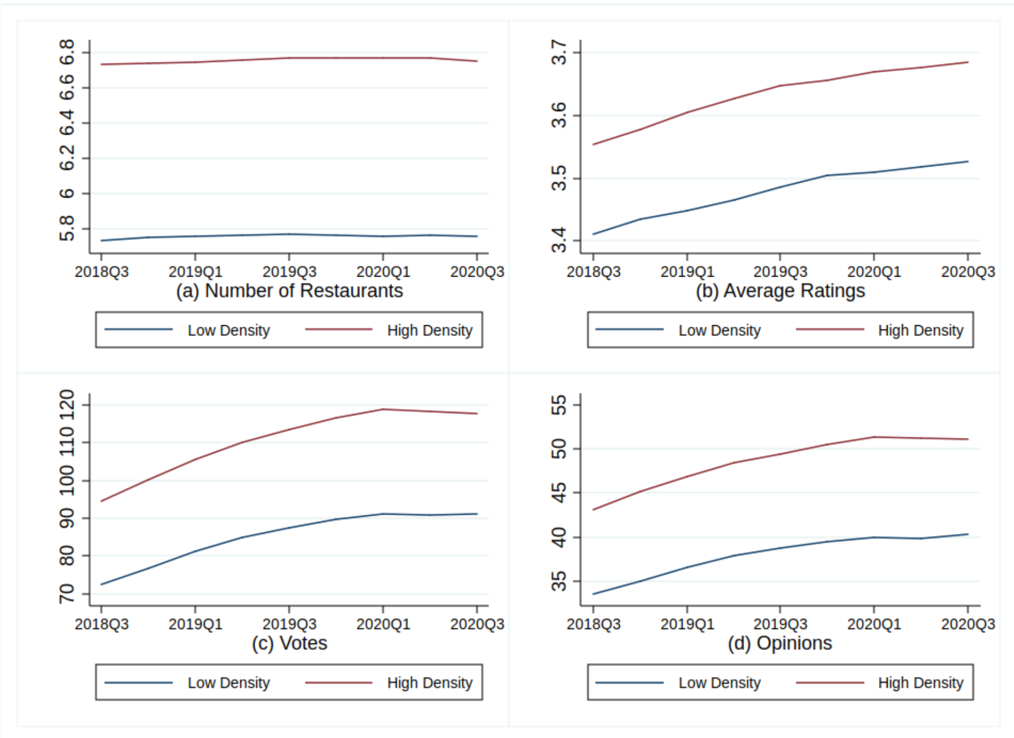


Figure 2: Trend for Outcome Variables

In Table 1, we report descriptive statistics of all the variables used in the event studies and baseline regressions that focus on the city of Lisbon, from the third quarter of 2018 until the third quarter of 2020.

Table 1: Descriptive Statistics on Sample Characteristics for Lisbon

	N	Mean	St. Deviation	Min	Max
Number of Civil Parishes	24	-	-	-	-
A. Short-term Rentals					
Density of Short-term Rental Accommodations	24	0.071	(0.111)	0.001	0.440
B.Restaurants					
Number of Restaurants	61,108	-	-	-	-
Price of a Meal For Two (€)	61,108	21.792	(16.471)	3	340
Ratings	61,108	3.558	(0.675)	1	5
Votes/Likes	61,108	98.219	272.293	1	5858
Opinions/Comments	61,108	43.441	(116.995)	0	2692

Notes: Panel A. *Short-term Rentals* describes statistics for the data set from RNAL, with information on short-term rental registries in Lisbon in 2019. Panel B. *Restaurants* describes statistics for the data set from Zomato, with information on restaurants in Lisbon, since 2018 until 2020.

Tables 6 and 7, extracted from Batalha et al. 2022, are reproduced in the Appendix, presenting comparative statistics of the treatment and control groups in terms of several characteristics, such as short-term rental markets, political preferences, socioeconomic and demographic characteristics, as well as amenities. Naturally, the short-term rental density differs between the two groups. The population density and the share of highly educated residents are not statistically different across the two groups.

In regards to the characteristics of the restaurants in Lisbon, out of the 7,787, around 54% in our data set belong to the Dining section, whereas only 6% and 8%, respectively, are Bars and Pastries. Cafés constitute, approximately, 24% of the restaurants supply of Lisbon. For treated areas, taking into account 3,684 restaurants, these percentages do not change much: Dining compose 57% of the food establishment supply, while Bars and Pastries hold 9% and 6%, respectively. Cafés constitute, approximately, 20% of the restaurants supply of the treated areas.

5 Results

The main results of our empirical approach are presented in this section. Additionally, we perform five robustness checks.

5.1 Baseline Results

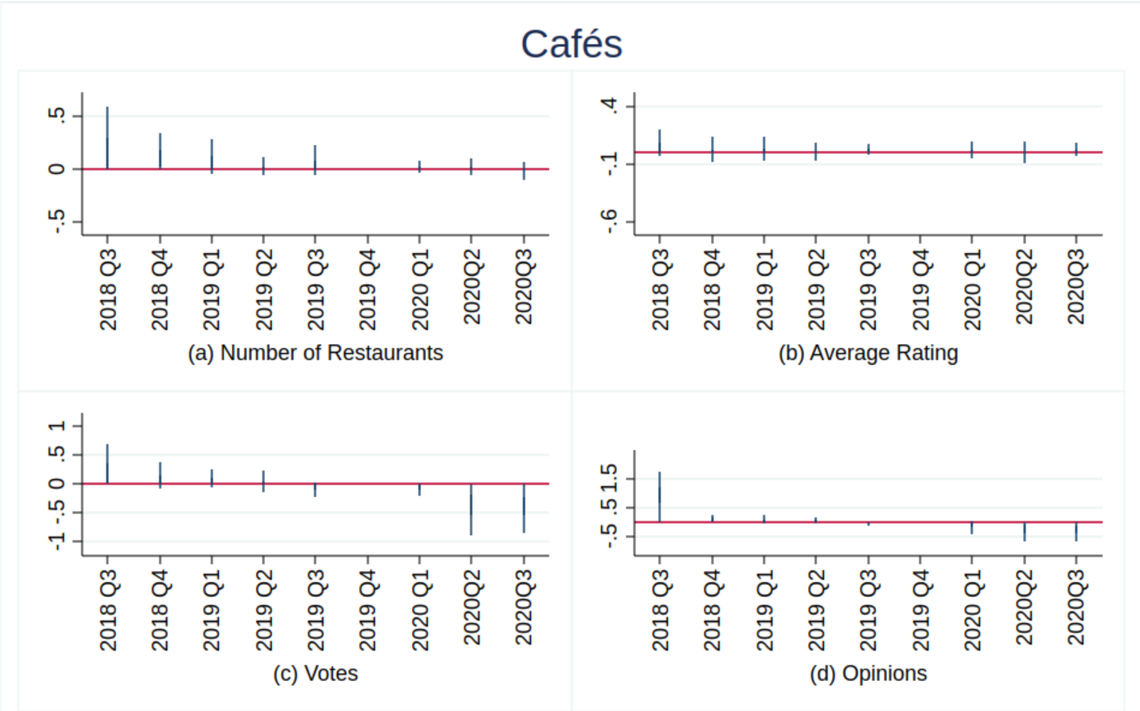
The set of results assesses the impact of the COVID-19 pandemic on the number of restaurants per civil parish; the average ratings attributed to each restaurant; as well as the number of likes and comments shared within the platform per restaurants. To verify the parallel trends assumption, we conduct event studies for Lisbon's civil parishes. Figures 3 to 9 plot the values of the continuous interaction coefficient $Post_q \times Density_p$, for the city of Lisbon, for Dining restaurants, Bars, Cafés, and Pastries, respectively. Note how, across the four variables of interest, in all four food establishment types, parallel trends, at large, hold. After the treatment, across all four types of food establishments, likes present the most substantial variations out of the four variables of interest. The downward trend indicates that Zomato users are hitting the *like* bottom less often; most probably, because restaurants were less available too. The other indication of platform interaction (i.e., comments) also shows a declining trend, especially for the smaller establishments (Cafés and Pastries), but not as strongly as its likes counterparts. Number of restaurants and average ratings appear to increase slightly for Bars, while remaining unchanged for Dining restaurants and Cafés. Pastries present a decrease in the number of establishments and an upwards trend in the average ratings. The binary approach produces much less broad results, although still statistically significant. These are presented in Figures 4 to 10, in the Appendix. The fact that both continuous and binary treatments produce comparable results, although with different magnitudes, further corroborates the reliability of our conclusions.

Figure 3: Event Studies for Dining - Continuous

Figure 4: Event Studies for Dining - Binary

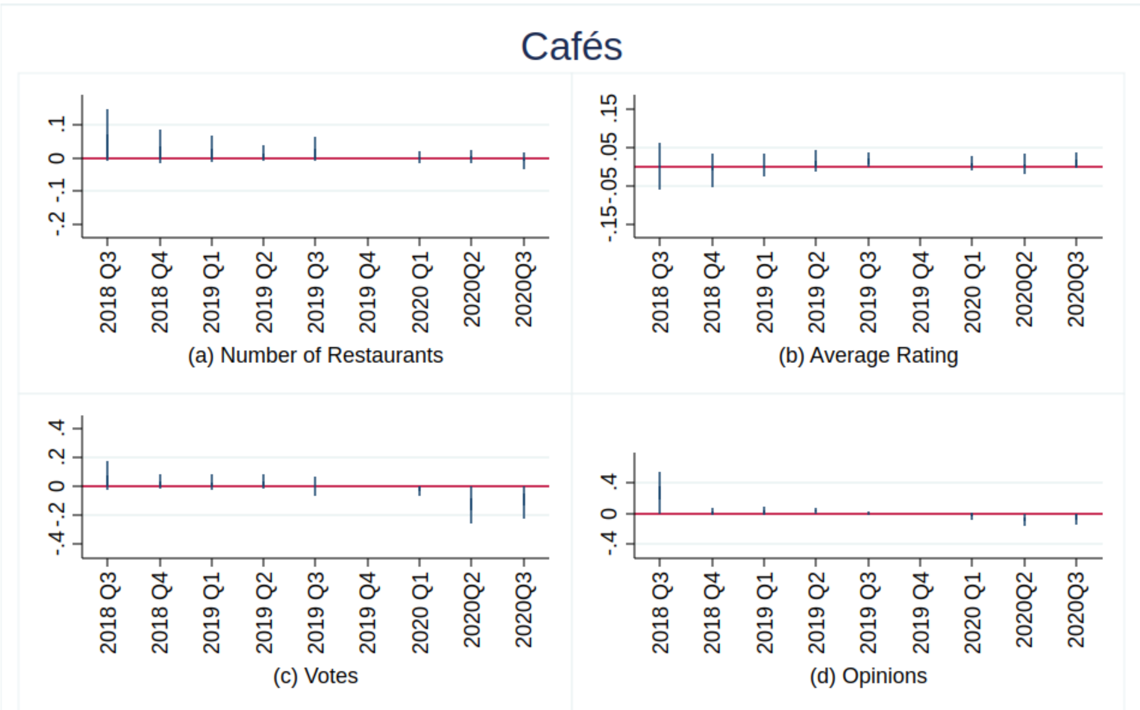
Figure 5: Event Studies for Bars - Continuous

Figure 6: Event Studies for Bars - Binary



In Panel (a) N=216 and Panels(b)-(d) N= 88,646.
The comparison group consists of the 17 low short-term rental density civil parishes.
The regression includes quarter and civil parishes fixed effects. The treatment period starts in 2020Q1.
95% confidence intervals.

Figure 7: Event Studies for Cafés - Continuous



In Panel (a) N=216 and Panels(b)-(d) N= 88,646.
The comparison group consists of the 17 low short-term rental density civil parishes.
The regression includes quarter and civil parishes fixed effects. The treatment period starts in 2020Q1.
95% confidence intervals.

Figure 8: Event Studies for Cafés - Binary

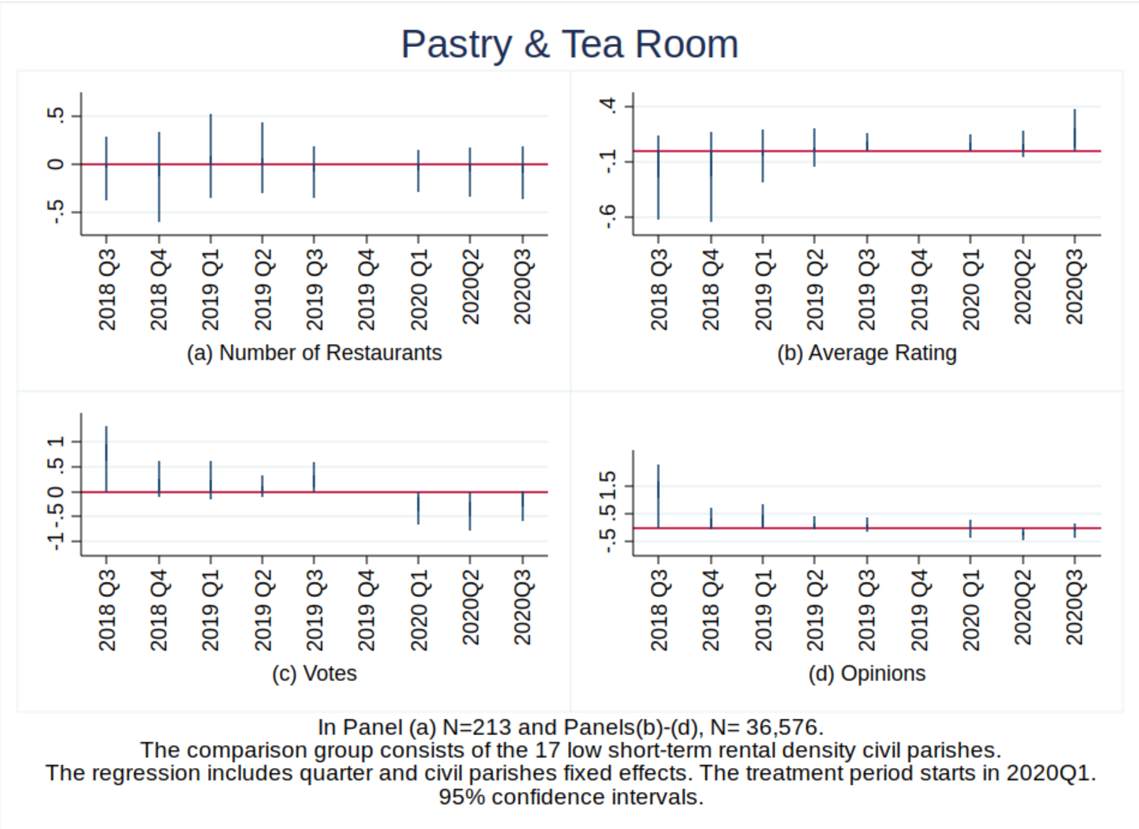


Figure 9: Event Studies for Pastries - Continuous

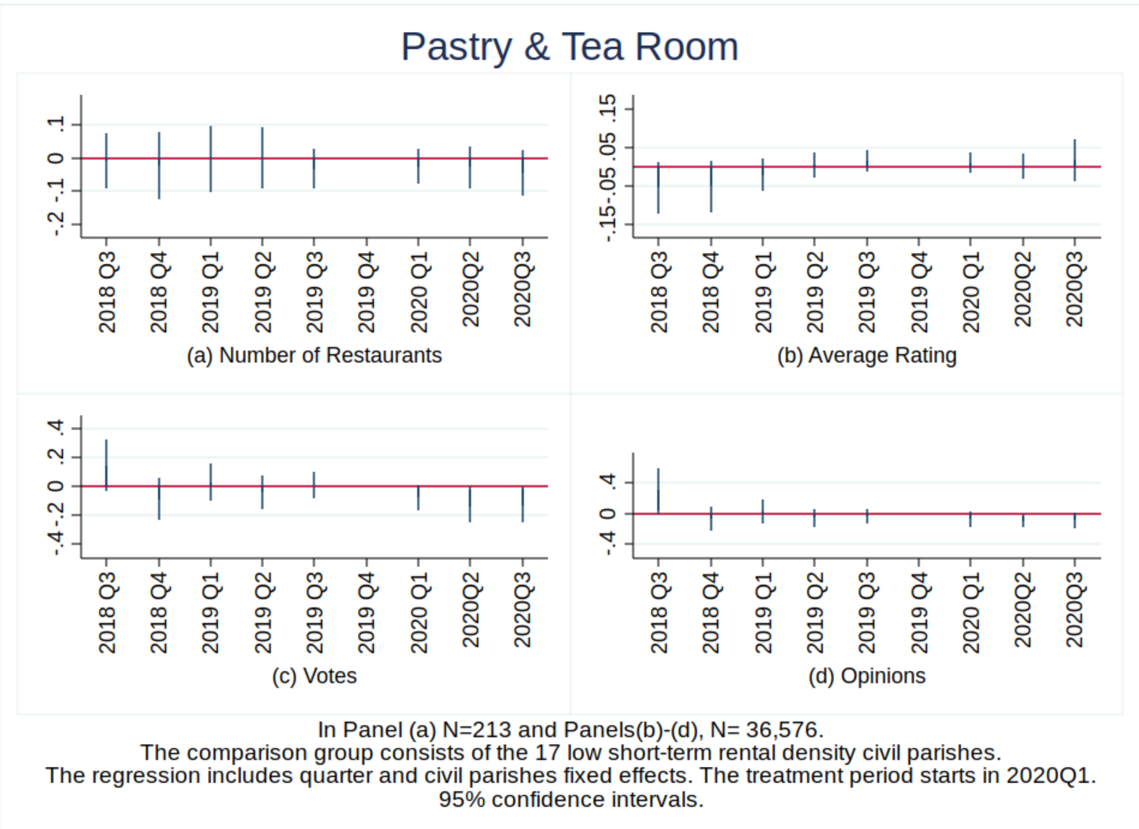


Figure 10: Event Studies for Pastries - Binary

We present our baseline results, obtained from estimating Equation 2, in Tables 2 to 5. Columns 1 to 4 show the results for the continuous treatment, whereas columns 5 to 8 present the binary results. The first two tables present no significant results. This indicates that, for our variables of interest, for both Dining restaurants and Bars, there appears to be a little-to-no impact of the pandemic, in the period being evaluated. As for the remaining two tables (4 and 5), the results are significant, for both continuous and binary treatments, for the platform interaction indicators: likes and comments. On average, all else equal, for Cafés, likes and comments fell by 48.6% and 56.1%, respectively. Besides, in the treatment group, likes and comments fell by 14% and 15%, respectively, for Cafés, on average, *ceteris paribus.* All of these results are significant at 1% level of significance. For Pastries, on average, both likes and comments fall too, by 69.6% and 56.1%, respectively, all else held constant, at 1% level of significance. In the treatment group, at 10% significance level, likes fall by 12.6%; while comments, at 5% level of significance, decrease by 12%, on average, all else equal. We can also see a significant decrease in the average ratings of Pastries, which fell 0.176 points, at 10% level of significance, on average, all else held constant.

Overall, our results suggest a considerable impact of the pandemic on the restaurant sector. Although the number of establishments remained the same, all other variables of interest took harsh hits, especially the interaction-with-the-platform indicators. The virus forced several, long stops in the sector. Even when establishments could reopen, the rules were strict enough to still keep some customers away (e.g., limited number of people allowed inside and/or mandatory curfew at 11pm). Perhaps layoffs and other governments transfers (e.g., iVauchers) to food establishment owners kept the businesses alive, but it would be reckless to assume that they were left in good shape. The decrease in the level of engagement with the peer-to-peer platform evidently shows that less and less customers entered through the restaurants doors.

Table 2: Difference in Differences - Dining - Lisbon

	Continuous				Binary			
	Number	Ratings	Likes	Comments	Number	Ratings	Likes	Comments
Post · Density	4.5839	-0.0041	-0.0451	-0.0707	2.850	0.005	-0.015	-0.024
	(11.286)	(0.3312)	(0.2902))	(0.2487)	(2.495)	(0.010)	(0.060)	(0.054)
Civil Parish FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	216	32,110	32,110	32,110	216	32,110	32,110	32,110
R-squared	0.999	0.0408	0.3672	0.3371	0.999	0.041	0.367	0.337

Notes: The treated civil parishes are *Avenidas Novas, Arroios, Estrela, Misericórdia, Santa Maria Maior, Santo António, São Vicente*. Robust standard errors are depicted in parenthesis. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Difference in Differences - Bar + Cocktail Bar + Pub + Wine Bar - Lisbon

	Continuous				Binary			
	Number	Ratings	Likes	Comments	Number	Ratings	Likes	Comments
Post · Density	3.759	0.025	0.071	0.040	1.339	0.035	0.061	0.066
	(0.256)	(0.091)	(0.253)	(0.220)	(1.023)	(0.035)	(0.090)	(0.077)
Civil Parish FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	216	32,110	32,110	32,110	189	3,647	3,647	3,647
R-squared	0.999	0.081	0.463	0.408	0.999	0.081	0.463	0.401

Notes: The treated civil parishes are *Avenidas Novas, Arroios, Estrela, Misericórdia, Santa Maria Maior, Santo António, São Vicente*. Robust standard errors are depicted in parenthesis. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Difference in Differences - Cafés + Snack Bar + Quick Bites - Lisbon

	Continuous				Binary			
	Number	Ratings	Likes	Comments	Number	Ratings	Likes	Comments
Post · Density	-0.112	-0.012	-0.486***	-0.561***	0.030	0.005	-0.14***	-0.15***
	(0.080)	(0.063)	(0.165)	(0.204)	(0.020)	(0.019)	(0.040)	(0.046)
Civil Parish FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	216	32,110	32,110	32,110	216	14,453	14,453	14,453
R-squared	0.999	0.031	0.450	0.227	0.996	0.031	0.450	0.227

Notes: The treated civil parishes are *Avenidas Novas, Arroios, Estrela, Misericórdia, Santa Maria Maior, Santo António, São Vicente*. Robust standard errors are depicted in parenthesis. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Difference in Differences - Pastry Shop and Tea Room - Lisbon

	Continuous				Binary			
	Number	Ratings	Likes	Comments	Number	Ratings	Likes	Comments
Post · Density	-0.061	-0.176**	-0.696***	-0.561***	-0.022	0.027	-0.126*	-0.12**
	(0.172)	(0.095)	(0.139)	(0.107)	(0.043)	(0.028)	(0.063)	(0.046)
Civil Parish FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	216	32,110	32,110	32,110	213	4,945	4,944	4,944
R-squared	0.989	0.064	0.535	0.468	0.989	0.064	0.534	0.4671

Notes: The treated civil parishes are *Avenidas Novas, Arroios, Estrela, Misericórdia, Santa Maria Maior, Santo António, São Vicente*. Robust standard errors are depicted in parenthesis. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.2 Robustness Checks

In this subsection, we present four exercises to examine the reliability of our baseline results.

The first one consists of including the seven civil parishes in Porto, Portugal's second largest city. To assign civil parishes to the treated group, we exploit the fact that a ban on new short-term rental registries was also introduced in Porto, in 2019. The results are robust. In fact, with the inclusion of Porto's parishes, there is a statistically significant decrease in the number of Cafés. We show our findings in the Appendix, in Tables 8 to 11.

In the second robustness test, we replicate our baseline specification excluding data from the first quarter of 2020. Since the pandemic in Portugal started in March 2020, and anticipation effects in the previous two months are unlikely to play an impactful role, we investigate whether our baseline results depend on the inclusion of this quarter. Once again, the results are robust. They are shown in Tables 12 to 15, in the Appendix.

In the third robustness test, we exclude the third quarter of 2020 from our data. This is because there was a reopening of many food establishments around this period, coinciding with the summer time, making this quarter somewhat different than the remaining. We test whether our baseline results depend on the inclusion of this quarter as well. These results are shown in Tables 16 to 19, in the Appendix - and are, too, robust.

The fourth robustness test involves selecting special parishes, with different characteristics than the remaining. As observable in Tables 6 and 7, in the Appendix, buildings in treated areas are, on average, older, which is consistent with the fact that they are closer to the historical city centre. In Tables 20 to 23, shown in the Appendix, we present results excluding the civil parishes with the most recent constructions from the comparison areas: Parque das Nações, Olivais, Lumiar, Carnide, and Santa Clara. In these five parishes of the external Northern border of the city, half of the housing stock was built after the 1970s, and almost 40% after the 1980s. The results are robust.

6 Conclusion

With the boom in tourism and the saturation of traditional information channels, online platforms, such as Airbnb and Zomato, are spreading fast through a system of peer-to-peer, where comments, reviews, and likes can tell much more than, for instance, a conventional TV ad. This generates adjustments in the way individuals and, consequently, cities organize themselves, including changes on both the real estate market and the business landscape. The global pandemic accelerated the platformization of economic sectors (Ferreira et al. 2022), highlighting even further the power of these apps and websites to create deep and significant transformations in the backbone of cosmopolitan and capital cities, such as Lisbon, one of the 100 most visited cities in the world[13].

This paper studies the effect of short-term rental listings on the local economic activity of the city of Lisbon. We do so by exploiting the outbreak of the COVID-19 pandemic, comparing civil parishes with a higher density of short-term rentals with the remaining ones. We examined high-quality data on both short-term rental registries and Zomato entries in Lisbon, aggregated at the parish level. The results show that the pandemic led to a considerable decrease in the indicators of demand/barometers of interaction between the consumers and the online restaurant-aggregator, Zomato. The very-famous like button saw a decrease of almost 70% in some food establishments, for example. For Pastry Shops

[13]See https://www.idealista.pt/en/news/lifestyle-portugal/2019/10/09/432-lisbon-and-porto-are-between-100-most-visited-cities-world

and Tea Rooms, there are also some decreases in the overall ratings, accompanied by a fall in both likes and comments. This is convincing evidence that the restaurant sector took a quite hard hit during the lockdown. Moreover, it comes to prove that restrictive policies (whether within the scope of the short-term rental market or the restaurant sector) might have unforeseen, yet significant, impacts on both individuals and cities.

Our findings can contribute to a more informed debate about the consequences of the spread of these peer-to-peer platforms, as they have indeed the ability to go beyond our smartphones and actually affect our lives and policy tools. Barometers of interaction respond to the negative demand shock quite quickly and strongly. Our results indicate that the collapse of the short-term rental market is responsible for over a half of the fall in likes for some food establishments in the city of Lisbon in the period post-pandemic. Additionally, the policies designed to limit the size of the short-term rental market in Lisbon - some of which have already been in place since 2018 - should also take into account how that can have an impact on the quantity and quality of the businesses and amenities the city offers its tourists and, most importantly, its inhabitants and long-term residents. Other public policies that may have an impact in the real estate market and the restaurant sector are interesting topics for future research.

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A Figures

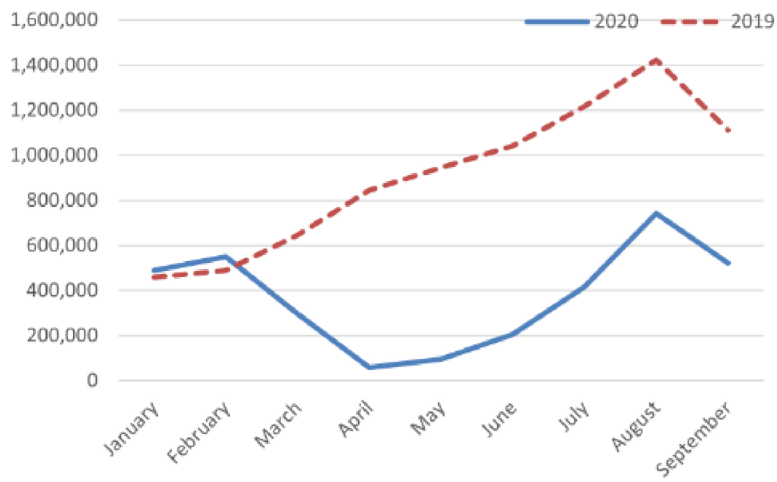

Figure 11: Overnight Stays in Short-term Rental Accommodations in Portugal
Source: Statistics Portugal

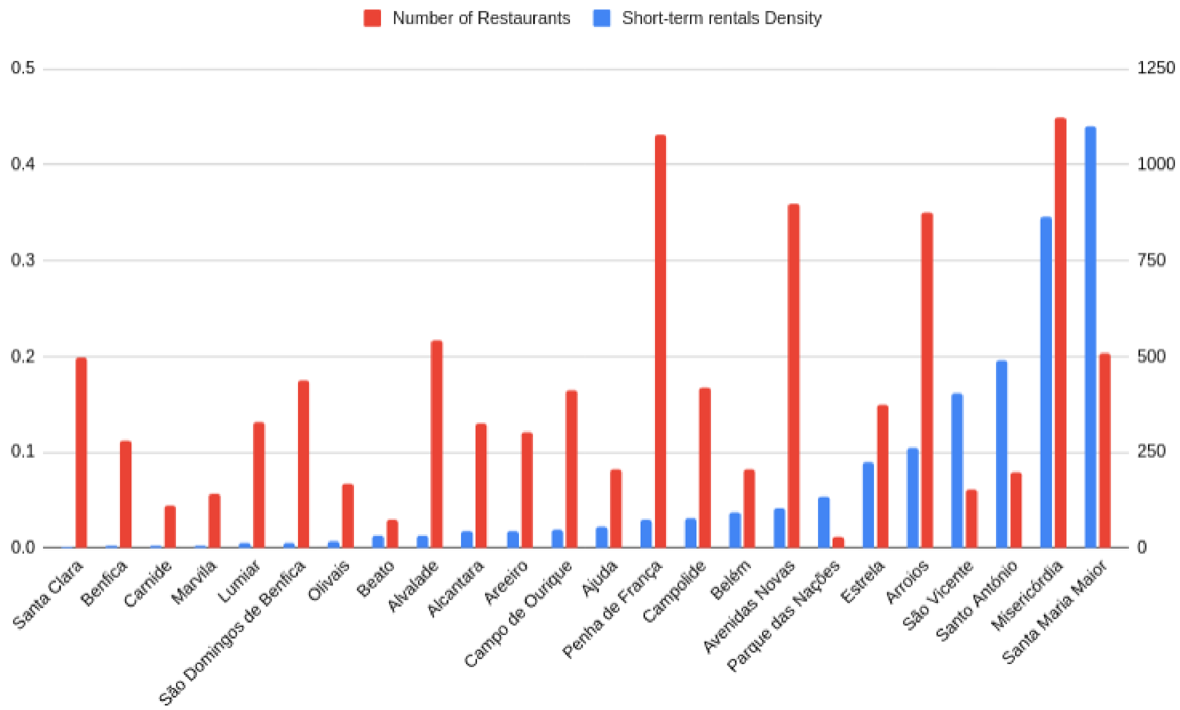

Figure 12: Short-term Rental Accommodation Densities (on the left axis) and Number of Restaurants (on the right axis) for each parish in Lisbon in 2019
Sources: RNAL and Zomato

Figure 13: Map of the seven Porto parishes, where the two treated are in black.

B Tables

Table 6: Balance Tests

	Pre-Treatment			
	High Density	Low Density	Difference	Source & Date
Number of Civil Parishes	7	17	-	
Density of Short-term Rental Accommodations	0.19	0.02	0.176***	RNAL 2019
			(0.01)	
A.Demographics and Socio-economic Characteristics				
Population Density (No./km2)	7119.472	6246.160	873.313	Census 2011
			(0.610)	
Commuting time (in minutes)	21.945	22.320	-0.375	Census 2011
			(0.767)	
% Under 15 years-old	0.111	0.126	-0.015*	Census 2011
			(0.088)	
% Above 65 years-old	0.249	0.230	0.019	Census 2011
			((0.241)	
% Cannot read	0.031	0.032	-0.001	Census 2011
			(0.884)	
% Higher Education	0.334	0.297	0.038	Census 2011
			(0.405)	
% Turnout Local Election	0.550	0.530	0.020	SGMAI 2017
			(0.311)	
% Students with State Support	0.412	0.440	-0.027	CML 2017/2018
			(0.648)	
% Average Daily Value Withdrawn in ATMs (€)	336,502.813	285,008.375	51,494.434	SIBS Sep 2017
			(0.543)	
% Average Daily Number of Withdrawals in ATMs	6,286.162	4,976.902	1,409.260	SIBS Sep 2017
			(0.330)	

Table 7: Balance Tests - Cont.

	Pre-Treatment			
	High Density	Low Density	Difference	Source & Date
B.Amenities				
Valmor Awards	14	10	4	CML 2018
			(0.432)	
ATM Devices	68.286	45.471	22.815	SIBS Sep 2017
			(0.160)	
Retailers	11	10	1	Sales Index 2018
			(0.846)	
Price of a Meal for Two (€)	28.696	26.430	2.266***	Zomato Q4 2019
			(0.001)	
Votes/Likes	150.853	130.421	20.431*	Zomato Q4 2019
			(0.081)	
Opinions/Comments	65.419	57.127	8.292*	Zomato Q4 2019
			(0.093)	
Amount Spend on Construction Works by CML (M€)	15.956	12.285	3.670	CML 2012-2018
			(0.385)	
Construction Works by CML	56	52.706	3.294	CML 2012-2018
			(0.830)	

Notes: The control group is composed by civil parishes in low density areas. P-values are displayed between parenthesis considering standard errors clustered per civil parish. CML (Câmara Municipal de Lisboa) is the Town Hall. SIBS (Sociedade Interbancária de Serviços) is the main provider and manager of electronic payment services in Portugal[14]. Census 2011 are available from Statistics Portugal. SGMAI (Secretaria-Geral do Ministerio da Administração Interna) is the government body responsible for election data. RNAL (Registo Nacional de Alojamento Local) is the National Short-Term Rental Registry. Valmor Awards is a Portuguese architectural award granted to buildings.

Table 8: Difference in Differences - Dining - Porto

	Continuous				Binary			
	Number	Ratings	Likes	Comments	Number	Ratings	Likes	Comments
Post · Density	2.787	0.001	-0.022	-0.025	2.784	0.001	-0.022	-0.025
	(1.988)	(0.009)	(0.0.051)	(0.045)	(1.988)	(0.009)	(0.051)	(0.045)
Civil Parish FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	279	40,662	40,661	40,661	279	40,662	40,661	40,661
R-squared	0.999	0.042	0.368	0.346	0.999	0.042	0.368	0.346

Notes: The treated civil parishes are *Avenidas Novas, Arroios, Estrela, Misericórdia, Santa Maria Maior, Santo António, São Vicente, Bonfim, and Cedofeita, Santo Ildefonso, Sé, Miragaia, São Nicolau e Vitória.* Robust standard errors are depicted in parenthesis. Significance Levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 9: Difference in Differences - Bar + Cocktail Bar + Pub + Wine Bar - Porto

	Continuous				Binary			
	Number	Ratings	Likes	Comments	Number	Ratings	Likes	Comments
Post · Density	3.965	-0.006	0.161	0.137	0.922	0.34	0.076	0.083
	(3.087)	(0.060)	(0.175))	(0.155)	(0.723)	(0.028)	(0.077)	(0.064)
Civil Parish FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	252	4,914	4,914	4,914	252	4,914	4,914	4,914
R-squared	0.999	0.082	0.461	0.419	0.999	0.083	0.461	0.419

Notes: The treated civil parishes are *Avenidas Novas, Arroios, Estrela, Misericórdia, Santa Maria Maior, Santo António, São Vicente, Bonfim, and Cedofeita, Santo Ildefonso, Sé, Miragaia, São Nicolau e Vitória.* Robust standard errors are depicted in parenthesis. Significance Levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 10: Difference in Differences - Cafés + Snack Bar + Quick Bites - Porto

	Continuous				Binary			
	Number	Ratings	Likes	Comments	Number	Ratings	Likes	Comments
$Post \cdot Density$	-0.132*	0.010	-0.348	-0.339	-0.041**	0.008	-0.178***	-0.185***
	(0.073)	(0.061)	(0.209)	(0.243)	(0.017)	(0.015)	(0.050)	(0.056)
Civil Parish FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	279	18,800	18,800	18,800	279	18,800	18,800	18,800
R-squared	0.996	0.063	0.416	0.250	0.996	0.063	0.3417	0.251

Notes: The treated civil parishes are *Avenidas Novas, Arroios, Estrela, Misericórdia, Santa Maria Maior, Santo António, São Vicente, Bonfim, and Cedofeita, Santo Ildefonso, Sé, Miragaia, São Nicolau e Vitória.* Robust standard errors are depicted in parenthesis. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Difference in Differences - Pastry Shop and Tea Room - Porto

	Continuous				Binary			
	Number	Ratings	Likes	Comments	Number	Ratings	Likes	Comments
$Post \cdot Density$	-0.074	0.203*	-0.789***	-0.622***	-0.027	0.013	-0.136**	-0.137***
	(0.148)	(0.088)	(0.142)	(0.127)	(0.033)	(0.025)	(0.065)	(0.047)
Civil Parish FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	276	6,942	6,941	6,941	276	6,942	6,941	6,941
R-squared	0.990	0.093	0.513	0.459	0.991	0.093	0.512	0.459

Notes: The treated civil parishes are *Avenidas Novas, Arroios, Estrela, Misericórdia, Santa Maria Maior, Santo António, São Vicente, Bonfim, and Cedofeita, Santo Ildefonso, Sé, Miragaia, São Nicolau e Vitória.* Robust standard errors are depicted in parenthesis. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Difference in Differences - Dining - Lisbon - Without 2020Q1

	Continuous				Binary			
	Number	Ratings	Likes	Comments	Number	Ratings	Likes	Comments
$Post \cdot Density$	0.009	-0.023	-0.058	-0.074	2.158	0.002	-0.016	-0.023
	(0.069)	(0.032)	(0.282)	(0.237)	(0.720)	(0.827)	(0.784)	(0.656)
Civil Parish FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	192	32,880	32,880	32,880	192	32,880	32,880	32,880
R-squared	0.998	0.041	0.368	0.338	0.999	0.041	0.368	0.338

Notes: The treated civil parishes are *Avenidas Novas, Arroios, Estrela, Misericórdia, Santa Maria Maior, Santo António, São Vicente*. Robust standard errors are depicted in parenthesis. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Difference in Differences - Bar + Cocktail Bar + Pub + Wine Bar - Lisbon - Without 2020Q1

	Continuous				Binary			
	Number	Ratings	Likes	Comments	Number	Ratings	Likes	Comments
$Post \cdot Density$	3.200	0.055	0.120	0.075	1.107	0.039	0.128	0.122
	(0.278)	(0.606)	(0.626)	(0.719)	(0.254)	(0.259)	(0.178)	(0.115)
Civil Parish FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	168	3,581	3,581	3,581	168	3,581	3,581	3,581
R-squared	0.999	0.081	0.464	0.409	0.999	0.809	0.465	0.410

Notes: The treated civil parishes are *Avenidas Novas, Arroios, Estrela, Misericórdia, Santa Maria Maior, Santo António, São Vicente*. Robust standard errors are depicted in parenthesis. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 14: Difference in Differences - Cafés + Snack Bar + Quick Bites - Lisbon - Without 2020Q1

	Continuous				Binary			
	Number	Ratings	Likes	Comments	Number	Ratings	Likes	Comments
$Post \cdot Density$	-0.116	-0.055	-0.528***	-0.579**	0.031	0.002	-0.149***	-0.155***
	(0.082)	(0.073)	(0.177)	(0.211)	(0.021)	(0.023)	(0.048)	(0.051)
Civil Parish FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	192	13,866	13,866	13,866	192	13,866	13,866	13,866
R-squared	0.996	0.031	0.462	0.232	0.996	0.031	0.462	0.232

Notes: The treated civil parishes are *Avenidas Novas, Arroios, Estrela, Misericórdia, Santa Maria Maior, Santo António, São Vicente*. Robust standard errors are depicted in parenthesis. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 15: Difference in Differences - Pastry Shop and Tea Room - Lisbon - Without 2020Q1

	Continuous				Binary			
	Number	Ratings	Likes	Comments	Number	Ratings	Likes	Comments
$Post \cdot Density$	-0.067	-0.164*	-0.730***	-0.621***	-0.026	0.022	-0.132*	-0.122**
	(0.173)	(0.082)	(0.129)	(0.127)	(0.045)	(0.026)	(0.065)	(0.049)
Civil Parish FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	190	4,927	4,926	4,926	190	4,927	4,926	4,926
R-squared	0.990	0.064	0.536	0.469	0.990	0.064	0.535	0.468

Notes: The treated civil parishes are *Avenidas Novas, Arroios, Estrela, Misericórdia, Santa Maria Maior, Santo António, São Vicente*. Robust standard errors are depicted in parenthesis. Significance Levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 16: Difference in Differences - Dining - Lisbon - Without 2020Q3

	Continuous				Binary			
	Number	Ratings	Likes	Comments	Number	Ratings	Likes	Comments
$Post \cdot Density$	0.015	-0.024	-0.052	-0.078	3.919*	0.002	-0.014	-0.024
	(0.055)	(0.033)	(0.278)	(0.240)	(0.427)	(0.011)	(0.058)	(0.052)
Civil Parish FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	192	31,884	31,884	31,884	192	31,884	31,884	31,884
R-squared	0.999	0.041	0.366	0.337	0.999	0.041	0.366	0.337

Notes: The treated civil parishes are *Avenidas Novas, Arroios, Estrela, Misericórdia, Santa Maria Maior, Santo António, São Vicente*. Robust standard errors are depicted in parenthesis. Significance Levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 17: Difference in Differences - Bar + Cocktail Bar + Pub + Wine Bar - Lisbon - Without 2020Q3

	Continuous				Binary			
	Number	Ratings	Likes	Comments	Number	Ratings	Likes	Comments
$Post \cdot Density$	4.574	0.066	0.075	0.062	0.286	0.038	0.114	0.118
	(2.951)	(0.101)	(0.242)	(0.212)	(0.256)	(0.034)	(0.091)	(0.175)
Civil Parish FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	168	3,581	3,581	3,581	168	3,581	3,581	3,581
R-squared	0.999	0.081	0.464	0.409	0.999	0.809	0.465	0.410

Notes: The treated civil parishes are *Avenidas Novas, Arroios, Estrela, Misericórdia, Santa Maria Maior, Santo António, São Vicente*. Robust standard errors are depicted in parenthesis. Significance Levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 18: Difference in Differences - Cafés + Snack Bar + Quick Bites - Lisbon - Without 2020Q3

	Continuous				Binary			
	Number	Ratings	Likes	Comments	Number	Ratings	Likes	Comments
$Post \cdot Density$	-0.099	-0.040	-0.462**	-0.543**	-0.026	0.003	-0.130***	-0.144***
	(0.077)	(0.073)	(0.166)	(0.202)	(0.019)	(0.022)	(0.042)	(0.048)
Civil Parish FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	192	13,860	13,860	13,860	192	13,860	13,860	13,860
R-squared	0.996	0.031	0.454	0.231	0.996	0.031	0.454	0.230

Notes: The treated civil parishes are *Avenidas Novas, Arroios, Estrela, Misericórdia, Santa Maria Maior, Santo António, São Vicente*. Robust standard errors are depicted in parenthesis. Significance Levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 19: Difference in Differences - Pastry Shop and Tea Room - Lisbon - Without 2020Q3

	Continuous				Binary			
	Number	Ratings	Likes	Comments	Number	Ratings	Likes	Comments
$Post \cdot Density$	-0.056	-0.146	-0.723***	-0.615***	-0.015	0.022	-0.127*	0.121**
	(0.169)	(0.090)	(0.148)	(0.100)	(0.042)	(0.026)	(0.066)	(0.048)
Civil Parish FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	190	4,924	4,923	4,923	190	4,924	4,923	4,923
R-squared	0.990	0.064	0.536	0.468	0.990	0.064	0.535	0.468

Notes: The treated civil parishes are *Avenidas Novas, Arroios, Estrela, Misericórdia, Santa Maria Maior, Santo António, São Vicente*. Robust standard errors are depicted in parenthesis. Significance Levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 20: Difference in Differences - Dining - Lisbon - Without Northern Parishes

	Continuous				Binary			
	Number	Ratings	Likes	Comments	Number	Ratings	Likes	Comments
$Post \cdot Density$	0.034	-0.018	-0.060	-0.091	2.734	-0.001	-0.029	-0.043
	(0.050)	(0.035)	(0.296)	(0.255)	(2.536)	(0.011)	(0.063)	(0.056)
Civil Parish FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	171	28,781	28,781	28,781	171	28,781	28,781	28,781
R-squared	0.999	0.038	0.365	0.334	0.999	0.038	0.365	0.334

Notes: The treated civil parishes are *Avenidas Novas, Arroios, Estrela, Misericórdia, Santa Maria Maior, Santo António, São Vicente*. Robust standard errors are depicted in parenthesis. Significance Levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 21: Difference in Differences - Bar + Cocktail Bar + Pub + Wine Bar - Lisbon - Without Northern Parishes

	Continuous				Binary			
	Number	Ratings	Likes	Comments	Number	Ratings	Likes	Comments
Post · Density	4.144	0.048	-0.048	0.044	1.510	0.054	0.073	0.095
	(0.316)	(0.094)	(0.224)	(0.203)	(0.909)	(0.034)	(0.082)	(0.069)
Civil Parish FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	153	3,479	3,479	3,479	153	3,479	3,479	3,479
R-squared	0.999	0.062	0.459	0.405	0.999	0.062	0.459	0.406

Notes: The treated civil parishes are *Avenidas Novas, Arroios, Estrela, Misericórdia, Santa Maria Maior, Santo António, São Vicente*. Robust standard errors are depicted in parenthesis. Significance Levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 22: Difference in Differences - Cafés + Snack Bar + Quick Bites - Lisbon - Without Northern Parishes

	Continuous				Binary			
	Number	Ratings	Likes	Comments	Number	Ratings	Likes	Comments
Post · Density	-0.053	-0.008	-0.491**	-0.552**	-0.014	0.007	-0.147***	-0.152***
	(0.063)	(0.068)	(0.174)	(0.210)	(0.016)	(0.021)	(0.042)	(0.049)
Civil Parish FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	171	12,567	12,567	12,567	171	12,567	12,567	12,567
R-squared	0.997	0.061	0.535	0.472	0.997	0.028	0.442	0.221

Notes: The treated civil parishes are *Avenidas Novas, Arroios, Estrela, Misericórdia, Santa Maria Maior, Santo António, São Vicente*. Robust standard errors are depicted in parenthesis. Significance Levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 23: Difference in Differences - Pastry Shop and Tea Room - Lisbon - Without Northern Parishes

	Continuous				Binary			
	Number	Ratings	Likes	Comments	Number	Ratings	Likes	Comments
Post · Density	-0.153	-0.194*	-0.600***	-0.524***	-0.044	0.034	-0.091*	0.096*
	(0.172)	(0.106)	(0.134)	(0.098)	(0.047)	(0.034)	(0.063)	(0.048)
Civil Parish FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	171	4,180	4,180	4,180	171	4,180	4,180	4,180
R-squared	0.991	0.061	0.535	0.472	0.991	0.061	0.535	0.471

Notes: The treated civil parishes are *Avenidas Novas, Arroios, Estrela, Misericórdia, Santa Maria Maior, Santo António, São Vicente*. Robust standard errors are depicted in parenthesis. Significance Levels: * p < 0.10, ** p < 0.05, *** p < 0.01.