Shared Prosperity (or Lack Thereof) in the Sharing Economy

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This paper examines the heterogeneous economic spillover effects of a home sharing platform—Airbnb—on the growth of a complimentary local service—restaurants. By circumventing traditional land-use regulation and providing access to underutilized inventory, Airbnb is attracting the visitors of a city to vicinities that are not traditional tourist destinations. Although visitors generally bring significant spending power, it is, however, not clear if the visitors use Airbnb primarily for lodging, thus, not contributing to the local economy. To evaluate this, we focus on the impact of Airbnb on the employment growth of New York City (NYC) restaurants. Our results indicate that if the intensity of Airbnb activity (Airbnb reviews per household) increases by 2%, the restaurant employment in that neighborhood grows by approximately 3%. We use algorithmic matching in combination with a difference-in-difference (DID) specification that utilizes the spatial and temporal differences in Airbnb entry into NYC neighborhoods. We validate the underlying mechanism behind this result by evaluating the impact of Airbnb on Yelp visitor reviews. In particular, neighborhoods with increasing Airbnb activity also experience a surge in their share of NYC visitor reviews. This result is further validated by evaluating the impact of a unique Airbnb neighborhood level policy recently implemented in New Orleans. We also investigate the role of demographics and market concentration in driving the variation. Notably, restaurants in areas with a relatively high number of Black residents do not benefit from the economic spillover of Airbnb activity.

Key words: The Sharing Economy, Employment Growth, Racial Disparity

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1. Introduction

The rapid growth of the sharing economy—44% of Americans have participated in the sharing economy as of 2016—and its impact on local economies is a topic of discussion among practitioners, regulators, and researchers.[1] Much of this attention has focused on the sharing economy's impact on traditional economic activity that directly competes with a platform—e.g., Uber on the taxi industry (Cramer and Krueger 2016, Wallsten 2015)

[1] http://time.com/4169532/sharing-economy-poll/

and Airbnb on the hotel industry (Zervas et al. 2017). Other work has focused on the potentially negative spillover effects of home sharing platforms on the housing markets in large cities (Barron et al. 2018, Sheppard and Udell 2016). Further studies have found a spillover effect on entrepreneurial activity (Burtch et al. 2018), durable goods market (Gong et al. 2018), and interactions between different sharing economy products (Zhang et al. 2018). In contrast, we focus on the economic spillover effects of home sharing platforms, specifically Airbnb, on local non-competing complimentary economic establishments.

Home sharing platforms such as Airbnb connect residents of a city with potential visitors/tourists. Through the platform, visitors find acceptable hosts to stay with during their visit and the hosts receive compensation for allowing the visitors to stay in their home. By providing access to underutilized inventory (Einav et al. 2016), home sharing platforms have the potential to redistribute/attract the visitors of a city to vicinities without a significant hotel presence. Hosts who use these platforms are not restricted by land-use regulations and large fixed costs, allowing them to provide accommodations to visitors in areas that would otherwise have been infeasible (Coles et al. 2018). Figure 1 shows the distribution of hotels, Airbnb activity, and restaurants in New York City (by zipcode) in 2015. The majority of hotels are centrally located while Airbnb stays are more geographically distributed. In other words, Airbnb visitors have the opportunity to, and do, locate in areas without a significant hotel presence.

Visitors that choose to locate in these sharing economy enabled areas have two options. On the one hand, they may exploit the area in which they are lodging strictly for accommodation purposes and commute to more traditional tourist locations. As a result, they will spend their non-accommodation based tourism dollars in the traditional tourist locations. On the other hand, they may go beyond staying in an area and spend their tourism dollars locally. To evaluate the economic spillover effect of this spending, we focus on restaurants in New York City (NYC). NYC is the most visited city in the United States and, in 2012, 21% of tourist spending in NYC, or \$7.4 billion, was spent at restaurants.[2] Only accommodation (\$10 billion) and shopping (\$8 billion) expenditures accounted for a higher proportion of tourist spending.[3] As shown in Figure 1, the geographic distribution of restaurants is dispersed across the whole city. This implies that while some areas may

[2] http://www.thisisinsider.com/most-visited-us-cities-2017-12#2-los-angeles-california-9

[3] https://skift.com/2013/07/09/how-tourists-to-new-york-city-spend-their-money/

not have a large hotel presence, all areas, for the most part, have a significant restaurant presence. Therefore, if a home-sharing visitor chooses to locate in areas without a hotel presence, they would still have access to a substantial number of local restaurants. If the home-sharing visitors in these areas do utilize local restaurants, then these restaurants will improve their financial performance. This improvement would be reflected in the aggregate area level restaurant employment. Consequently, due to both the significance of restaurants with regard to tourist spending and the dispersed geographic distribution of restaurants across NYC, we ask the following research question: *What is the impact of home-sharing activity on local restaurant employment growth? Does this effect vary across areas and, if so, what are the local drivers of this heterogeneous impact?*

Importantly, even in the cases where visitors using home-sharing platform choose to utilize the local area for more than simply accommodation services, the new visitors' impact on local restaurants is still uncertain. There are a multitude of factors that will influence the magnitude of this effect. For example, unlike the majority of traditional accommodation alternatives in the hospitality industry (hotels/motels), home-sharing services often provide access to the host's kitchen. This option enables visitors to forgo restaurants and prepare their meals in their homes, which would reduce the potential impact of home-sharing visitors on local restaurants.

Another factor that will determine the impact of the home-sharing platform on local restaurants is the potential impact of home-sharing visitors on the dynamics of local restaurant demand and its subsequent impact on local residents' behavior. Depending on the agreement, the Airbnb visitor may occupy the home without the host being present or the visitor may share the home with the host during their stay. These two alternatives present different ramifications for the potential demand for local restaurants. The visitors that do not share the homes with the hosts during their stay are consequently replacing the host for the duration of their visit. This temporarily alters the dynamics of local restaurant demand but does not necessarily impact the size of the market. Conversely, visitors that share the homes with the hosts are potentially affecting both the size and dynamics of the restaurant market. Also, since home-sharing listings are often in areas that do not traditionally cater to visitors/tourists, there is a potential for these new home-sharing enabled visitors to affect local residents' behavior as well. For example, a resident's utility to frequent a local restaurant may decrease as more visitors frequent that restaurant. Moreover, even in the case where the visitor displaces the host, the host has obtained access to additional financing through the short term rental income. Therefore, while the host is temporarily unavailable, they also have more income to potentially spend on restaurants when they are not renting out their homes.

To empirically identify the impact of home-sharing induced visitor redistribution on local restaurant employment, we must account for endogenous underlying factors that simultaneously affect the popularity of home sharing and restaurants. To address this concern, we first remove neighborhoods with significant tourism activity in the years preceding Airbnb entry. Second, we employ a difference-in-difference (DID) specification which utilizes the fact that restaurant employment data is available for the years prior to Airbnb entry into NYC and that not all areas in NYC have significant Airbnb activity. The DID approach extracts the difference in area level restaurant employment before and after Airbnb entry in neighborhoods with high levels of Airbnb activity. The second difference in the DID framework compares this difference in high intensity Airbnb areas with the analogous difference in low intensity Airbnb areas.

The specification incorporates fixed effects and local variables. These variables create a framework whereby Airbnb intensity is conditionally exogenous to the local factors that may impact restaurant employment. Specifically, the panel structure of this approach incorporates area level fixed effects which rule out the effect of potentially endogenous unobserved time invariant local attributes. We also include a time effect which captures city and/or national factors which may impact local economic activity across NYC during a specific time period. We augment these controls with time varying local area characteristics such as retail employment, hotel employment, and local restaurant popularity. As further validation, we utilize matching algorithms to pair areas with a higher intensity of Airbnb activity with comparable areas with lower intensity of Airbnb activity.

Our results indicate that if the intensity of Airbnb activity (Airbnb reviews per household) increases by 2%, then the restaurant employment in that neighborhood grows by approximately 3%. This result is validated across multiple specifications including aggregation at the zipcode level instead of the neighborhood level and a specification using algorithmic matching with zipcodes. We also conduct various robustness checks to assess the definitions of Airbnb intensity, restaurant employment, and matching metrics. To examine the generalizability of this result to other cities, we expand our analysis to an additional 5 major U.S. cities and find similar results.

The mechanism behind these findings is evaluated by assessing the impact of Airbnb activity on Yelp visitor reviews. We find that if the intensity of Airbnb activity (Airbnb reviews per household) increases by 2%, then the proportion of NYC Yelp visitor reviews that occur in that neighborhood increases by approximately 7%. The mechanism is corroborated by an examination of a neighborhood level policy shift by New Orleans in 2017. New Orleans implemented a policy whereby Airbnb was deemed illegal in one neighborhood while it was officially legalizing in adjacent neighborhoods. The policy shift caused the proportion of Yelp visitor reviews in the newly legalized neighborhood to increase and simulataesly decrease in the illegal neighborhood. In summary, our results indicate a three stage process: 1) Airbnb reviews redistribute visitors to areas that would not otherwise have had access to visitor spending 2) The redistributed Airbnb visitors frequent local restaurants and 3) The redistributed Airbnb visitors that frequent local restaurants have a tangible economic impact on the performance of the restaurants in these neighborhoods.

To delineate the intricacies of Airbnb's effect across localities, we investigate the role of demographics and market concentration in driving the variation. Our results suggest that both demographics and market structure have an important role in determining the areas that benefit from the economic spillover of Airbnb. Notably, restaurants in areas with a relatively high number of Black residents or a relatively high number of Hispanic residents do not benefit from the economic spillover of Airbnb activity. This trend continues when expanding the results to cities beyond NYC, especially as it pertains to the lack of spillover affect in majority Black localities. An exception to this trend is Los Angeles, which has 49% Hispanic population; the impact of home sharing on restaurant employment does extend to majority Hispanic areas. For the market structure heterogeneity analysis, we use local Yelp reviews to identify the concentration of restaurant activity in certain areas. We find that in areas where a few restaurants capture the majority of local Yelp reviews—high concentration areas—the impact of Airbnb on restaurant employment is diminished.

The sharing economy has altered the landscape of many traditional industries. As regulators struggle with ways to frame legislative discussions surrounding its impact, it is imperative to also assess the economic spillover these alternatives create. This is crucial as regulators seek to obtain a holistic picture of the sharing economy's impact. We provide evidence to the importance of this discussion by establishing a positive economic spillover effect of home sharing on restaurant employment. Perhaps most critically to the regulatory discussion, this benefit is not homogeneous. This implies that a focus on purely the negative direct effects of these platforms may be shortsighted. Furthermore, any discussion surrounding positive spillover benefits must be tempered by an understanding that these benefits are not homogeneously benefiting all localities.

2. Empirical Context

2.1. Geographic Aggregation Levels

Our empirical context is NYC Airbnb activity, restaurant reviews on Yelp written by visitors to NYC, and restaurant employment from the year 2005 to 2015. We obtain restaurant employment data from the Bureau of Labor Statistics (BLS) Business Pattern Data.[4] This data provides the number of employees in the restaurant industry by zipcode for a specific year.[5] Our data ends in 2015 as this is the last year of publically available Business Pattern Data at the time of writing. We also obtain local demographic data from the U.S. Census Bureau. This includes race, origin, median income, and number of households. We aggregate the data at two levels: neighborhood and zipcode with each aggregation level providing specific advantages.

Neighborhoods are large enough to be self-sufficient if a visitor wishes to remain locally, but are also not so large that it would be impossible for a visitor to choose to commute to other neighborhoods if they desire. Furthermore, neighborhoods are organized in a manner so as to represent similar economic, demographic, and market structure characteristics. We determine neighborhoods based on the boundaries indicated by the New York State Department of Health.[6] The report splits NYC into 42 neighborhoods and allocates each zipcode in NYC to a neighborhood. Table 1 outlines the summary statistics of the neighborhoods in our sample.

[4] We include the following institution categories and their associated NAICS codes in defining the restaurant sector: full-service restaurants (722511), limited-service restaurants (722513), drinking places (722410), cafeteria and grill buffets and buffets (722514), and snack and nonalcoholic beverage bars (722515). URL: https://www.naics.com/six-digit- naics/?code=72

[5] This is not an exact number of employees in each restaurant, but rather a range of the number of employees. For example, at each zipcode level, we have the number of restaurants with 1 - 4 employees, 5- 10 employees, and so on. We multiply the number of institutions in each area by the midpoint of the associated employee range, and then sum for across levels within a zipcode. For example, a zip code with 3 institutions of 1-4 employees and 3 institutions of 5-10 employees would have a total number of employees of 3*2.5+ 3*7.5 = 30.

[6] https://www.health.ny.gov/statistics/cancer/registry/appendix/neighborhoods.htm

We also conduct our analysis at the zipcode level. We use zipcodes due to the greater variation in local economic and demographic characteristics of zipcodes relative to neighborhoods and the larger number of zipcodes. This enables us to conduct an algorithmic matching procedure which is not possible at the neighborhood level due to the smaller number of neighborhoods and the limited variation between them.

2.2. Home Sharing Platform Data from Airbnb

We obtain consumer facing data from Airbnb, the most prominent home sharing platform in the world.[7] Specifically, we gather Airbnb listings and review data for NYC. We utilize web crawlers to periodically gather this data and combine it with data from insideairbnb.com, which is a website providing access to periodic crawls of Airbnb listings and reviews.[8] To validate the accuracy of the data collected we reproduce results from Coles et al. (2018), who study Airbnb usage and growth patterns in NYC and have access to proprietary data obtained from Airbnb. Our analysis indicates that our data patterns follows the patterns found in the proprietary Airbnb data obtained by the authors.

Airbnb allows hosts to list their properties, either whole homes or just rooms in their homes, on their online platform and potential visitors can choose from the selection of listings. Visitors that utilize the platform and, subsequently, stay at a listing are asked to review the hosts/listings after their stays and have 14 days to submit their reviews.[9] We use the total number of reviews written for hosts with listings in a specific area and specific time period as a proxy for Airbnb demand. This method has been used in prior research (Barron et al. 2018, Horn and Merante 2017, Zervas et al. 2017) and, furthermore, the variation in reviews follows similar patterns to Coles et al. (2018), who use proprietary data from Airbnb in NYC.

The Airbnb website was launched in 2008 (at the time it was called Airbedandbreakfast.com). Figure 2 displays the Airbnb entry year for NYC zipcodes from 2008 to 2012. Airbnb entry occurs temporally, however, even among the Airbnb active zipcodes, the relative intensity of the activity is not uniform. Figure 3 outlines the year in which the ratio of the number of Airbnb reviews in a zipcode by the number of housing units in that zipcode

[7] www.airbnb.com

[8] http://insideairbnb.com/get-the-data.html

[9] https://www.airbnb.com/help/article/13/how-do-reviews-work

was greater than 2%.[10] This measure—Airbnb reviews per housing unit—defines Airbnb intensity in this paper. Furthermore, Table 2 presents a summary of the reviews collected from Airbnb. The statistics are displayed at both the neighborhood and zipcode aggregation levels. The table also shows the proportion of reviews that are associated with private listings and the proportion associated with shared listings. Private listings are where the Airbnb visitor obtains access to a complete housing unit without the host's presence. A shared listings is where the visitor must share certain amenities with the host and/or other guests. By 2015, the data shows that not all zipcodes have Airbnb activity. With regard to neighborhoods, Northeast Queens has the least Airbnb activity in 2015 with only 84 Airbnb reviews. The differences in Airbnb entry years and the different Airbnb intensities across areas enable us to utilize a DID specification with the Airbnb intensity measure representing the continuous treatment effect. By utilizing a continuous treatment variable, we are able to determine the impact of Airbnb entry and intensity.

2.3. Restaurant Review Data from Yelp

We also obtain consumer facing data from restaurant reviews on Yelp. We use web crawlers to obtain this information during September 2017. We scrape all reviews from restaurants in NYC. Yelp reviews are used as a proxy for local restaurant economic activity (Glaeser et al. 2017, 2018). We also scrape every review ever written by each reviewer in our sample. These include reviews written for restaurants in NYC and out of NYC. By doing so, we have access to two important data features. First, we are able capture the reviews for the NYC restaurants that were closed at the time of our collection.[11] Therefore, if a restaurant is open in a previous year, but was closed at the time of our data collection, we would have review data for that restaurant for the period when it was open. Second, by obtaining all the reviewers' review histories, we can separate the reviewers into two categories: 1)

[10] In 2015, the median value of Airbnb per household for New York City neighborhoods was 2.3%.

[11] Yelp does not remove closed restaurant review pages from their directory, however they are removed from the main search page. The URL for these closed restaurants can be obtained through the review pages of reviewers that had previously reviewed these restaurants when they were open. Therefore, if a reviewer in our sample has previously reviewed a restaurant that is now closed, then we can access that restaurant's URL from the reviewer's review history page. As such, our process is as follows: (1) collect the reviews for the restaurants in our initial sample of restaurants obtained from crawling the Yelp main search page for NYC restaurants, (2) combine all the restaurant reviews and create a list of all unique reviewers, (3) collect all the reviews from each reviewer's review history page, (4) combine all the reviews from step 3 and create a list of NYC restaurants that were not scraped in step 1 (these are likely closed but could also be restaurants that were not obtained from the initial Yelp search (5) collect the reviews from these restaurants and repeat the process. The process is finished when the next set of restaurants obtained from the reviewers' review histories provides no new restaurants.

reviews written by visitors to NYC and 2) reviews written by residents of NYC. We refer to these as visitor and local reviewers respectively.

Each reviewer on Yelp lists their location. However, these self-reported locations can be misleading, especially for a city like NYC where the reviewers could be reporting their original locations. For example, a person originally from Seattle, WA who lives and works in NYC may list their location as Seattle. The reverse may apply for someone living in Seattle but that is originally from NYC. To resolve this issue, we use the review history of all the reviewers in our sample to identify their locations. We consider a reviewer local (resident of NYC) if their stated location is within NYC and 75% or more of their reviews are for restaurants located in NYC. We consider a reviewer a visitor if their stated location is not NYC and less than 75% of their reviews are for restaurants in NYC.

By separating the reviews into these two categories (visitors and locals), we can focus on the category of Yelp reviews that would be impacted by Airbnb visitors. Specifically, if Airbnb users have introduced a significant amount of new restaurant demand to an area, then that demand would be reflected in the number of visitor Yelp reviews. Table 3 shows the summary statistics for the Yelp reviews in our sample. We calculate the proportion of all NYC Yelp restaurant reviews written by visitors in a specific area and year to measure time varying visitor restaurant activity.

We obtain more than 3.5 million Yelp reviews corresponding to 34,331 restaurants in NYC (these include both open and closed restaurants). While our method of crawling restaurants is quite exhaustive, we use restaurant health inspection data obtained from the NYC Department of Health and Mental Hygiene (DOHMH) to corroborate the list of restaurants that we obtained. Figure 4 plots the number of restaurants in a zipcode for both the DOHMH data and the Yelp data. The plot indicates that there is relative consistency in the number of restaurants across the two data sets for a particular zipcode.

We also utilize the Yelp reviews to calculate a restaurant popularity index for each area and year combination. First, for each area (i) and month (t) combination we calculate the proportion of reviews written by residents of NYC that occurred in restaurants in area i. Specifically, this is calculated as follows: $\frac{\text{\# Yelp Local Reviews in area i}}{\text{\# of Yelp Local Reviews in NYC}}$. Second, we obtain the yearly average of this proportion for each area i. We refer to this as the *Prop. of NYC Local Yelp Reviews in Area* i. The area with the highest *Prop. of NYC Local Yelp Reviews in Area* i in the base year (2007) is used as a benchmark. Third, for a given year and area

i, we calculate the restaurant popularity index as follows: $\frac{\text{Prop. of NYC Local Yelp Reviews in Area i}}{\text{Prop. of Local Yelp Reviews in base area}}$. The restaurant popularity index is incorporated as a control in our model.

The restaurant popularity index is an extremely useful variable as it captures the time variant area level characteristics that are associated with the popularity of restaurants in an area. For example, if a very popular restaurant was to open in an area in time period $t+1$, then that area would likely see an increase in Yelp reviews. This new popular restaurant may attract patrons that are both locals and visitors. The visitors that frequent this new popular restaurant may not necessarily be lodging in the local area, but may simply be attracted to the restaurant due to its growing popularity. Therefore, this new restaurant will cause an increase in both local and visitor restaurant activity from period t to period $t+1$. In this case, attributing the increase in visitor reviews to Airbnb activity would be incorrect as the increase in popularity may also attract Airbnb users to the same area. By incorporating the restaurant popularity index we have controlled for the economic variation that causes this new popular restaurant to open in area i. Therefore, this rich control allows us to better isolate Airbnb visitors' impact from the more general local economic factors that drive restaurant employment growth.

3. Impact of Airbnb on Restaurant Employment

3.1. Neighborhood Level Analysis

NYC is the largest tourist destination in the United States, and as a result, contains neighborhoods that were and continue to be established tourist destinations. That is, these areas attract a considerable amount of visitors with or without the presence of Airbnb. To identify the areas with endogenous local characteristics that attracted a large number of visitors before and after Airbnb, we examine the distribution of Yelp visitor reviews in 2008. Since Airbnb had negligible presence in 2008, Yelp visitor review activity in that year cannot be attributed to Airbnb visitors. The left graph in Figure 5 plots the number of Yelp visitor reviews for a neighborhood in 2008 and the number of Airbnb reviews in 2015. The areas with the largest number of Yelp visitor reviews in 2008 have, by far, the largest number of Airbnb reviews. Figure 6 displays the box plot of the 2008 Yelp visitor reviews across the 42 neighborhoods in our sample. We use the box plot to identify and remove outliers and refer to the new subsample of neighborhoods as the pruned sample.[12]

[12] Outliers include neighborhoods such as the Chelsea and Clinton neighborhood in lower Manhattan which attracted a substantial number of visitors in the periods prior to Airbnb arrival.

Ideally, for each level of visitor reviews in 2008, there should be neighborhoods with high and low Airbnb intensity in 2015. The right graph in Figure 5 shows the plot of 2008 Yelp visitor reviews against 2015 Airbnb reviews for the pruned sample of neighborhoods. A comparison of the left and right plots in Figure 5 shows an improvement in this variation from the non-pruned to the pruned sample. To provide more information regarding the role of these removed neighborhoods, Table 4 shows the changes in Yelp visitor reviews in the removed neighborhoods (from 2008 to 2015). The removed neighborhoods accounted for almost 89% of Yelp visitor reviews in 2008. This dropped to 82% in 2015. This supports the notion that Airbnb is enabling visitors to access new neighborhoods in the city. In fact, the removed neighborhoods also accounted for 57% of Airbnb intensity in 2015, providing further evidence regarding the difficulty in disentangling the effect of Airbnb from the capacity for these areas to attract visitors (both Airbnb and non-Airbnb visitors). Therefore, by removing these neighborhoods from our sample, we subsequently create a more balanced sample of Airbnb active and inactive neighborhoods.

To assess the role of Airbnb on NYC restaurant employment, we use the following difference- in-difference (DID) specification :

$$log(Restaurant\ Employment)_{i,t} = \beta_0 + \alpha_i + \delta_t + \beta_1 \cdot \frac{Airbnb\ Reviews_{i,t}}{Households_{i,t}} + X_{i,t} + \epsilon_{i,t} \quad (1)$$

where i represents the neighborhood and t represents the year. Our variable of interest is $\frac{Airbnb\ Reviews_{i,t}}{Households_{i,t}}$, which is the ratio of the number of Airbnb reviews written for Airbnb listings to the number of households in neighborhood i during year t. We use this ratio as a proxy for Airbnb intensity in a neighborhood. In section 5, we conduct various robustness checks for this measure as a proxy for Airbnb entry and intensity.

α_i is a fixed effect for neighborhood i which captures time invariant unobserved local characteristics for each neighborhood. These include demographic and economic variables without significant year to year change such as median income, race, and origin of residents. For example, if two neighborhoods have large differences in the number of households, then this will impact the number of restaurants in the area and, as a result, the restaurant employment. As such, the neighborhood fixed effects capture the average level of employment in a neighborhood. Furthermore, δ_t is a fixed effect for the year. This captures unobserved factors that impact restaurant employment in NYC as a whole for a specific time period. For example, there may be a national event which increases the number of tourists that come to the United States which will positively impact all NYC neighborhoods in a year.

The vector $X_{i,t}$ is a vector of local time varying controls. This includes the local restaurant popularity index calculated from the Yelp reviews for restaurants in neighborhood i. As previously detailed, this variable captures the variation in restaurant employment that is not associated with the time varying underlying economic conditions that cause restaurant success in each neighborhood. We also include the number of active restaurants on Yelp in neighborhood i during time t.[13] We incorporate local market structure variables from the BLS Business Pattern Data. Specifically, we include the number of employees in the hotel industry and the number of employees in the retail industry. The number of hotel industry employees is correlated with both the number, size, and performance of hotels in an area. Therefore, this variable controls for the impact of an increase in visitors that are using hotels as opposed to Airbnb and are utilizing local restaurants. This is particularly important given that the number of hotels in NYC increased by 35% between 2004 and 2013 and that many of these new hotels were located outside of the central tourist areas.[14] The number of retail employees controls for the number, size, and performance of retail stores in a local neighborhood. This is correlated with improving retail establishment conditions and relates to overall improving economic conditions in an area. Finally, the error term $\epsilon_{i,t}$ is the unobserved random shock associated with a neighborhood (i) during a specific time (t). We calculate robust standard errors that allow $\epsilon_{i,t}$ to be correlated for a specific neighborhood i across time t (Moulton 1990).

Table 5 presents the results of Equation 1. Column 1 reports the results of the full specification with the full sample of neighborhoods. Column 2 of the table reports the results of the specification in Equation 1 with the pruned sample of neighborhoods (32) and only Airbnb activity $\left(\frac{Airbnb\ Reviews_{i,t}}{Households_{i,t}}\right)$, year effects (δ_t), and neighborhood fixed effects (α_t). Columns 3 adds controls for the local restaurant popularity index and *log(Active Restaurant)*. Column 4 incorporates local employment controls, specifically *log(Hotel Employees)* and *log(Retail Employees)*. Across all specifications, our results indicate that Airbnb has a positive and salient impact on restaurant employment in a neighborhood. The coefficient for the specification for the pruned sample with all the covariates (column 4) is 1.516. This

[13] We define a restaurant as active if it was reviewed in year t.

[14] http://prattcenter.net/sites/default/files/hotel_development_in_nyc_report-pratt_center-march_2015.pdf

result indicates that if the number of Airbnb reviews increases by 2%, then restaurant employment will increase by 3.03%.

To isolate the impact of Airbnb on the proportion of NYC Yelp visitor reviews, the specification in Equation 1 controls for time invariant neighborhood effects, year effects, as well as a multitude of time varying local factors. These time varying local factors include the local restaurant popularity index, which captures time varying local economic factors that impact restaurant performance. The exhaustive collection of controls in Equation 1 mitigates the possibility of endogenous correlation between Airbnb review activity and unobserved local economic variations. However, to further validate our findings and reduce model dependency biases, we utilize matching as a pretreatment process in the analysis (Ho et al. 2007). Since there are not enough neighborhoods to reasonably match neighborhoods algorithmically, we conduct matches in two parts. First, we manually match neighborhoods based on the Yelp visitor reviews in 2008. Second, we aggregate the data at the zipcode level and—utilizing the larger number of zipcodes in the sample—algorithmically match zipcodes and conduct the analysis at the zipcode level.

3.2. Neighborhood Level Matching

Our motivation for pruning the sample was to remove areas with endogenous characteristics associated with their capacity to attract visitors. However, to further assuage any remaining doubts regarding this effect, we can utilize matching. Specifically, we can identify neighborhoods with significant Airbnb activity and find similar neighborhoods without Airbnb presence. For example, assume there are two neighborhoods where each neighborhood is able to attract x amount of visitors in the period before Airbnb. The value of x is indicative of each neighborhood's capacity to attract visitors. We assume that, without Airbnb, each neighborhood would attract a relatively similar proportion of visitors in the future. However, if Airbnb became popular in only one of the neighborhoods, then the difference in restaurant performance is attributable to Airbnb's impact. Therefore, in our sample, we pair neighborhoods based on the number of Yelp reviews in 2008 and Airbnb intensity in 2015. Our goal is to pair neighborhoods that have similar Yelp visitor activity in 2008 but differing Airbnb intensity in 2015. Table 6 shows the number of 2008 Yelp reviews for each neighborhood in the pruned sample. Each neighborhood pair is assigned manually and displayed in column 3. Column 5 of Table 5 shows the results of specification 1 on only the 24 matched neighborhoods. The coefficient for Airbnb Reviews per

Household is positive and statistically significant providing further evidence of the impact of Airbnb on restaurant employment.

3.3. Zipcode Level Analysis

As previously indicated, the greater variation in zipcode data, as well as the larger number of zipcodes, enables us to utilize matching algorithms. However, before describing the matching process, we present the results for the specification in Equation 1 at the zipcode level of analysis. Our sample initially contains 167 zipcodes. As discussed in the neighborhood level analysis, there are local areas that have high levels of pre-Airbnb Yelp visitor activity, indicating that these areas have a substantial visitor presence regardless of the availability of Airbnb. As such, we remove all the zipcodes that are located in the identified neighborhoods in Table 4. These are the neighborhoods with a high number of Yelp visitor reviews in 2008. After this process, we have 123 remaining zipcodes.[15] Figure 7 plots the 2008 Yelp reviews and the 2015 Airbnb reviews for each zipcode. The left side is for the full sample of 167 zipcodes while the right hand side shows the pruned sample of 123 zipcodes. As in the neighborhood case, in an idealized setting, for each range of 2008 Yelp visitor reviews there should be zipcodes with and without significant Airbnb presence. The pruning of the high visitation areas improves this metric significantly, which is evident based on the right graph in Figure 7.

Table 7 shows the results of Equation 1 conducted at the zipcode level. Columns 1 shows the results for the full sample of zipcodes (167 zipcodes) and columns 2, 3, and 4 show the results for the pruned sample of zipcodes (123 zipcodes). Similarly to the neighborhood results outlined in Table 5, the results indicate that Airbnb has a positive and salient impact on restaurant employment at the zipcode level.

3.3.1. Zipcode Level Matching Our results have thus far shown that Airbnb has a positive impact on restaurant employment in NYC. This has been identified at both the neighborhood and zipcode aggregation levels. We have identified the effect of Airbnb by utilizing a DID framework that incorporates a rich set of controls including fixed effects and time varying local economic measures such as the number of Yelp reviews written by locals. We now proceed to evaluate the robustness of these finding with regard to any

[15] We also remove zipcodes that have fewer than 20 restaurants as the restaurants in these zipcodes will not realistically have significant employment shifts.

lingering endogeneity concerns regarding the conditional exogeneity assumption in the DID framework. That is, given the controls in our specification, does there remain an unobserved time varying factor that impacts both Airbnb and restaurant employment simultaneously. While this concern is unlikely given the aforementioned controls, we utilize algorithmic matching to examine the robustness of this claim and reduce model dependency biases (Ho et al. 2007, Imai et al. 2008).

With the reduced sample of zipcodes (123 zipcodes), we use matching to define a subset of the data where zipcodes with significant Airbnb activity are matched with zipcodes without significant Airbnb activity. By comparing areas with similar characteristics—except for Airbnb intensity—we remove biases associated with zipcodes that are not comparable to any other zipcodes in the sample in terms of their capacity to attract Airbnb visitors (Heckman et al. 1998). Before matching the zipcodes, we must select criteria under which we define each zipcode as either a treated or control zipcode. We use 2015 Airbnb activity to determine whether a zipcode is treated. Based on the distribution of 2015 Airbnb reviews per household (Airbnb intensity), we establish upper and lower treatment criteria. If a zipcode has more Airbnb intensity in 2015 than the upper treatment criterion, then that zipcode is considered treated. If a zipcode has less Airbnb intensity in 2015 than the lower treatment criterion, then that zipcode is considered a control. Zipcodes where the number of 2015 Airbnb reviews falls between the upper and lower treatment criteria are removed. Unavoidably, this measure of treatment is subjective. Therefore, to assuage doubts regarding model dependency, we present a complete sensitivity analysis for all matching results based on various treatment definitions.

To match treated and control zipcodes, we compare a set of pretreatment local variables. The pretreatment variables are selected so as to predict the probability of an area obtaining an amount of Airbnb reviews that is higher than the upper criteria mentioned above. Since pretreatment variables are designed to predict Airbnb activity, we focus on the year 2008, which is the year prior to significant Airbnb activity. First, we include the number of households in a neighborhood. Neighborhoods with more households have a larger pool of potential Airbnb supply and, as such, will likely have more Airbnb activity. We also include the number of retail establishments and hotels in the zipcode. Areas that have underlying foundational structures that attracted visitors before Airbnb are likely to attract a larger number of Airbnb visitors. Furthermore, drawing on findings from Quattrone et al. (2016), we include the ratio of homes that are rented and the median income of residents in a zipcode. Quattrone et al. (2016) find that these factors have a persistent effect on Airbnb intensity in London.

To conduct the pretreatment matching, we use the aforementioned pretreatment matching variables as the predictors in a logistic regression to obtain the conditional probability of treatment (Propensity Score) for each zipcode (Rosenbaum and Rubin 1983, Caliendo and Kopeinig 2008). For each treated zipcode, we find the nearest neighbor by comparing the conditional probability of treatment to a set of control zipcodes. We remove the zipcodes that are not matched. This leaves us with a reduced subsample of zipcodes where each zipcode with a high level of Airbnb activity is matched with a zipcode with low Airbnb activity. Specifically, we first identify the Airbnb intensity (Airbnb reviews to households) in 2015 of each zipcode. We then calculate the 70^{th} percentile of the distribution of 2015 Airbnb intensity levels (2.76%). Any zipcode with a level of Airbnb intensity that is greater than the 70^{th} percentile is defined as a treated zipcode. To identify control zipcodes we calculate the 35^{th} percentile of the distribution of 2015 Airbnb intensity (0.007%). A zipcode with 2015 Airbnb intensity that is lower than the 35^{th} percentile is defined as a control zipcode. All other zipcodes are discarded. Using the aforementioned Propensity Score, each treated zipcode is matched with a control, and the zipcodes that are not matched are discarded. This process results in a subset of 58 zipcodes.

Column 5 of Table 7 shows the results of Equation 1 on only the matched subsample. Once again, the results indicate a positive and salient impact of Airbnb activity on restaurant employment. The coefficient size for Airbnb Reviews per Household indicates that if the Airbnb intensity in a zipcode increases by 2%, then restaurant employment would increase by approximately 2.93%. This increase is similar to the analogous increase for neighborhoods (3.03%).

3.3.2. Zipcode Matching: Sensititivy Analysis Since the selection of treatment in our design is subjective, we conduct a sensitivity analysis on the upper and lower treatment criteria. Table 8 displays the estimated coefficient values for the *Airbnb Reviews per Household* variable from Equation 1 for different specifications of upper and lower treatment criteria based on the distribution of Airbnb intensity in 2015. Specifically, each row represents the minimum boundary for treatment based on whether the Airbnb intensity indicator (ratio of Airbnb activity to households) was greater than the respective treatment criteria for that zipcode in 2015. For example, the coefficient in the first row and first column represents a minimum treatment threshold corresponding to the 70^{th} percentile and a maximum untreated threshold corresponding to the 35^{th} percentile. This entails that only the upper 30^{th} percentile and lower 35^{th} percentile of observations (according to 2015 Airbnb intensity) will be considered in the matching phase. The matching phase will then match each of the treated zipcodes with an untreated zipcode for the specific treatment criteria. The results indicate that for all specifications of treatment criteria Airbnb has a positive impact on restaurant employment. The findings indicate that a 2% increase in Airbnb intensity results in an increase in restaurant employment between 2.65% and 3.01% at the zipcode level.

4. Evidence Supporting the Validity of the Underlying Mechanism

4.1. The Impact of Airbnb on Yelp Visitor Reviews

Our results across multiple specifications and aggregation levels indicate that Airbnb has a positive impact on restaurant employment. The necessary underlying mechanism is that Airbnb visitors' are frequenting local restaurants. Therefore, to evaluate the validity of this mechanism, we use the Yelp visitor data that we collected to assess the impact of Airbnb activity on Yelp visitors' restaurant review behavior. We utilize the following DID specification:

$$\frac{\textit{Yelp Visitor Reviews}_{i,t}}{\textit{Yelp Visitor Reviews}_{t}} = \beta_0 + \alpha_i + \delta_t + \beta_1 \cdot \frac{\textit{Airbnb Reviews}_{i,t}}{\textit{Households}_{i,t}} + X_{i,t} + \epsilon_{i,t} \quad (2)$$

This is the same specification as Equation 1 except that the dependent variable is the proportion of NYC Yelp visitor reviews that were written for restaurants in zipcode i. This captures the spatial distribution of restaurant visitor activity across NYC. If Airbnb activity is impacting restaurant employment, then the areas with increasing Airbnb activity should capture an increasing proportion of the NYC restaurant visitor activity. Similar to the restaurant employment analysis, we first conduct the analysis at the neighborhood level, followed by zipcode and algorithmic matching.

In parallel with our restaurant employment analysis, we control for neighborhood fixed effects (α_i), year fixed effects(δ_t), and a vector of local time varying controls $X_{i,t}$, which includes retail employment, hotel employment, and the number of active restaurants on Yelp. It also includes the restaurant local popularity index for neighborhood i. As previously detailed, this variable captures the variation in Airbnb that is not associated with the time varying underlying economic conditions that cause restaurant success in each neighborhood. Finally, the error term, $\epsilon_{i,t}$, is the unobserved random shock associated with a neighborhood (i) during a specific time (t). We calculate robust standard errors that allow $\epsilon_{i,t}$ to be correlated for a specific neighborhood.

Table 9 presents the results of Equation 2 at the neighborhood level. Column 1 of the table reports the results of the specification in Equation 2 for the pruned sample of neighborhoods, which is the sample that removes the tourist-centric neighborhoods. Column 2 reports the results of the manually matched sample of neighborhoods based on the information in Table 6. The results indicates that Airbnb has a positive and salient impact on the proportion of NYC Yelp visitor reviews written in a neighborhood. To provide economic interpretation for the coefficient (Airbnb Reviews per Household) we evaluate the effect on a hypothetical neighborhood where the proportion of NYC visitor reviews is 0.214%—the median value in 2012. If Airbnb intensity, as measured by *Airbnb Reviews per Household*, increased by 2% then the proportion of Yelp visitor restaurant reviews in this neighborhood would increase by 0.016%.[16] Given that the current proportion of NYC visitor reviews is 0.214%, this represents a 7.3% increase in the proportion of Yelp visitor reviews. Furthermore, given that NYC tourist restaurant spending was $7.4 billion in 2012, the extra 0.016% that would be captured by the median neighborhood would translate to approximately $1.2 million of extra tourist restaurant expenditure.

Columns 4 and 5 report the results for the zipcode aggregation level, both the pruned sample (column 4) and the matched sample (column 5). We also estimate equation 2 for the various treatment criteria that were explained in section 3.3.1. Table 10 shows the coefficient for Airbnb Reviews per Household from Equation 2 for the various treatment criteria. Across all specifications, the results indicate that, Airbnb has a positive and salient impact on the proportion of Yelp visitor reviews in a locality.

4.2. The Impact of Airbnb on Yelp Local Reviews

To isolate the impact of Airbnb on the proportion of NYC Yelp visitor reviews, we controlled for time invariant neighborhood effects, year effects, as well as a multitude of time varying local factors. While our results provide evidence regarding the impact of Airbnb activity on visitors' restaurant activity, its effect on the restaurant activity of residents

[16] This is based on results from the manually matched sample of neighborhoods, column 2 of Table 9.

remains uncertain. If the aforementioned controls have adequately captured the local activity that relates to the attractiveness of an area to both Airbnb visitors and restaurants, then Airbnb activity should not have a positive impact on the proportion of NYC local Yelp reviews. A positive effect would imply that local residents are frequenting restaurants more often because of Airbnb, which is unrealistic. However, it may be the case that Airbnb has a negative impact on residents' restaurant behavior, as opposed to no impact. First, Airbnb visitors that do not share their rented homes with the hosts are temporarily displacing local residents and reducing the potential market size of resident restaurant demand. Second, a local resident's utility associated with frequenting a local restaurant may be reduced if that restaurant is now becoming more popular among visitors.

To assess the impact of Airbnb on local demand, as well as further validating the effectiveness of the controls in specification 1, we replace the proportion of Yelp visitor reviews with the proportion of Yelp local reviews in Equation 2. Effectively, this may also be seen as a falsification test for the main mechanism. The following outlines this specification:

$$\frac{\textit{Yelp Local Reviews}_{i,t}}{\textit{Yelp Local Reviews}_{t}} = \beta_0 + \alpha_i + \delta_t + \beta_1 \cdot \frac{\textit{Airbnb Reviews}_{i,t}}{\textit{Households}_{i,t}} + X_{i,t} + \epsilon_{i,t} \quad (3)$$

The results are presented in Columns 3 (neighborhood level) and 6 (zipcode level) of Table 9. The impact of Airbnb intensity is negative for both specifications. It is not statistically different from zero at the neighborhood level and is significant with 90% confidence at the zipcode level. The magnitude of coefficients across specifications is smaller than the model for Yelp visitor reviews (specification 2). This indicates that while Airbnb has a positive and extremely salient impact on visitor activity, its impact on local resident activity is more volatile and leaning towards negative. Table 11 shows the sensitivity of this result to various treatment criteria for the matching analysis. The results support the findings of a negative leaning effect of Airbnb on local demand.

4.3. Evidence from a Policy Shift in New Orleans

Thus far, we have relied upon the time varying entry and intensity of Airbnb into various areas to identify its impact on local restaurant activity. We have incorporated various controls including area and time fixed effects as well as time varying local factors that impact restaurants. This DID specification, specifically given the rich set of controls, has provided a framework that utilizes the conditional exogeneity of Airbnb intensity to identify the causal impact. However, access to a setting with a regulatory based policy shift would relieve the need for conditional exogeneity and further validate the consistency of the results. This policy shift is not available in NYC, however, a neighborhood level policy on Airbnb legality was implemented recently in New Orleans. In 2017, after various discussions between New Orlean's officials and Airbnb, the New Orlean's City Council voted to legalize short-term rentals in the city (these had previously been illegal but Airbnb was active in the city regardless). However, to legally run a short term rental property the hosts are required to register with the city. The city offered various types of short term rental registration options. This new policy also included a ban on short term rentals in the French Quarter neighborhood, which is an extremely popular tourist destination.[17] New Orleans officials also claimed that they would fine those hosts that were not in compliance with the new regulation.

As a result of this new policy, Airbnb supply shifted heavily away from the French Quarter neighborhood, which had attracted a significant number of Airbnb listings and visitors due to the popularity of the location. At the same time, the Central Business District, a bordering neighborhood, experienced significant increases in Airbnb demand. Figure 8 shows the temporal impact of the policy on the proportion of Airbnb reviews associated with locations in the French Quarter and Central Business District neighborhoods respectively. The dashed lines represent the timing of the policy. The first dashed lines indicates the announcement of the upcoming policy (Q4:2016) and second is the actual implementation of the policy (Q2:2017). The graph indicates a clear impact of the policy on Airbnb activity in the two neighborhoods.

This policy provides a unique opportunity to further assess the underlying mechanism behind our results. An exogenous policy shock shifts Airbnb from one neighborhood to a nearby neighborhood. We can then evaluate the impact on Yelp visitor and local activity in the same time period. We collect Yelp restaurant reviews and Airbnb review data for New Orleans. We aggregate this data to the New Orleans neighborhood level based on the neighborhood definitions used by Airbnb.[18] Figure 9 plots the proportion of New Orleans

[17] This ban did not extend to all of the French Quarter as some streets were exempted from the ban due to zoning regulations.

[18] insideairbnb.com provides shapefiles they obtain from the Airbnb website which outline the boundaries for each neighborhood in a city. We use these boundaries to identify whether a restaurant is located in that neighborhood by mapping the geocoded location of a restaurant and the neighborhood boundaries.

Yelp visitor reviews that are captured by each neighborhood respectively. The x-axis represents the quarter and each year is plotted separately. This is to account for seasonal factors of demand. We are interested in the dashed line which represents 2017, the year that the policy was implemented. In the Central Business District, Yelp visitor review activity is mixed for all the years prior to 2017. However, in 2017, it has a significant increase across all quarters. Conversely, in the French Quarter, Yelp visitor reviews are decreasing. Consistent with our results, Airbnb activity appears to drive visitor restaurant behavior. We also assess the impact on local reviews in Figure 10 and find that the impact of the policy does not significantly vary the behavior of local residents.

5. Robustness Checks

5.1. Measure of Airbnb Demand

In our analysis, we have used the ratio of Airbnb reviews to households as a proxy for Airbnb intensity. The denominator (households) is used to normalize the Airbnb activity by the number of potential hosts in a zipcode. An alternative method to normalize Airbnb activity is to use the log of the number of Airbnb reviews to represent Airbnb intensity. A log-log framework would allow us to capture the impact of percent changes in Airbnb activity on our dependent variables of interest. However, Table 2 shows that the Airbnb activity is active but extremely small in a large portion of areas. At the neighborhood level, the median number of Airbnb reviews in 2010, 2011, 2012, and 2013 is 0, 2, 19, and 50 respectively. This is problematic as logarithmic transformations are susceptible to high sensitivity with small values. For example, between 2012 and 2013 the neighborhood of Southeast Queens increased its Airbnb activity from 8 to 37 reviews and the neighborhood of West Queens increased from 382 to 828. On a logarithmic scale the increase in Southeast Queens is approximately 1.5 and the increase in West Queens is approximately 0.77. If Airbnb is to have a positive effect on the dependent variable, then, according to the logarithmic scale, it should be more pronounced in Southeast Queens. However, this is unlikely given that there were only 29 more reviews.

While the ratio of Airbnb reviews to households does not suffer from the same problem, we replace the independent variable of interest in Equation 1 (*Airbnb Reviews per Household*) with *log(Airbnb Reviews)* to evaluate the robustness of our results to this method of normalization. Column 1 of Table 12 (neighborhood level) and Table 13 (zipcode level) show the results of this specification. Our results are robust to this definition of Airbnb intensity, and, indicate that an area that doubles its Airbnb activity increases its restaurant employment by 1.8%.

We also assess the robustness of our results to three alternative definitions for Airbnb treatment. The measures are calculated as follows: Measure 1) 0 if the ratio of Airbnb to households is less than 2%, otherwise *log(Airbnb Reviews)*. Measure 2) 0 if the ratio of Airbnb to households is less than 1%, otherwise 1. Measure 3) 0 if the ratio of Airbnb to households is less than 2%, otherwise 1. Columns 2-4 of Table 12 and Table 13 show the results of Equation 1 with alternative Airbnb measures. The results indicate that our analysis is robust to differing Airbnb intensity measures, including strict binary measures of treatment.

5.2. Measure of Restaurant Employment

To measure restaurant employment, we obtain data from the U.S. Bureau of Labor Statistics. Specifically, we include the following institution categories and their associated NAICS codes in defining the restaurant sector: full-service restaurants (722511), limited-service restaurants (722513), drinking places (722410), cafeteria and grill buffets and buffets (722514), and snack and nonalcoholic beverage bars (722515). To determine whether our results are robust to the selection of NAICS codes to measure restaurant employment, we create two new definitions. The first alternative definition includes only full-service restaurants and limited services restaurants. The second alternative definition adds drinking places to the first alternative. Table 13 shows the results of Equation 1 for the two alternative definitions of restaurant employment. The results are consistent with our main findings, providing evidence that our analysis is robust to alternative restaurant employment measures.

5.3. Placebo Test

To determine the robustness of our results to a potential spurious effect driven by serial correlation of restaurant employment with unobserved activity we implement a randomized treatment test (Bertrand et al. 2004). Specifically, we use the binary treatment allocation of Airbnb demand described in section 5.1 based on a 2% threshold for treatment. That is, if the number of Airbnb reviews by households for an area in a given year is greater than 2%, that area is considered treated. To perform the randomization we randomly assign a treatment year to each zipcode and estimate specification 1 with the Airbnb intensity defined as the randomly assigned treatment variable. We repeat this process for 1,000 iterations.

Figure 11 displays the distribution of the resulting coefficient values. The distribution is centered around zero which indicates that, if the treatment was randomly assigned, the resulting impact of Airbnb intensity on restaurant employment would be non-existent. Furthermore, we conduct a t-test that evaluates whether the mean of the distribution is statistically different than zero and obtain a p-value of 0.44. This indicates that we fail to reject the hypothesis that the mean of the Airbnb intensity coefficients from randomly assigned treatments is different from zero. Finally, the coefficient value for the same specification that we estimated in section 5.1 is 0.110 (column 4 of Table 13). Based on the distribution in Figure 11, the probability associated with obtaining this coefficient in a randomized framework is less than 0.001.

5.4. Robustness of Matching Method

In section 3.3.2, we utilized the propensity score of each matched unit as the distance metric to finding a matching zipcode. While propensity score as a matching metric is widely used in the literature (Dehejia and Wahba 2002), to further alleviate concerns regarding choice dependency, we repeat the analysis of 3.3.1 for two other distance metrics: Mahalanobis Distance and Coarsend Exact Matching (CEM) (Iacus et al. 2012). We present the sensitivity analysis of a Mahalanobis distance based matching analysis and CEM in Tables 15 and 16 respectively. The results indicate a similarly positive and salient impact of Airbnb on restaurant employment, alleviating potential concerns regarding the selection of distance metric in our matching analysis.

6. Heterogeneity Analysis

Our results indicate that home-sharing platforms have a salient spillover effect on the economic performance of local complimentary services, specifically restaurants. This effect captures the average impact of Airbnb across NYC areas. We extend this analysis by evaluating the role of area level heterogeneity in driving the relationship between Airbnb and restaurant employment. We focus specifically on two categories: demographics and market structure.

6.1. Heterogeneous Impact of Airbnb Due to Local Demographics

Ideally, the economic spillover effect that Airbnb provides to restaurants would be independent of the demographic characteristics of the locality. However, this may not be the case. Evidence already indicates that Airbnb hosts and visitors may be incorporating race into their decision making process when finding a match on the platform (Edelman et al. 2017).

To examine the role of demographics on the relationship between Airbnb and restaurant employment we partition the zipcodes in our data based on demographics. For each zipcode, we determine the proportion of residents that identify as White, Black, and/or Hispanic.[19] This includes people who identify with more than one race. Table 17 summarizes the distribution of each demographic for the zipcodes in our sample. We create three subsamples of zipcodes, one for each demographic group. Each subsample contains only zipcodes where the proportion of residents that identify with the related demographic is greater than 50%. For example, in the White subsample, only zipcodes where 50% or more of the residents are White is included. The same is done for Black and Hispanic respectively.

For each subsample, we estimate Equation 1 to determine the impact of Airbnb on restaurant employment in areas with a high presence of a certain demographic. To identify this impact, it is necessary that each subsample have areas with high and low Airbnb intensity respectively. In other words, each subsample should have areas with and without Airbnb activity. Table 17 shows the percentage of zipcodes within each subsample where the Airbnb intensity is high (Airbnb per household is greater than 2% in 2015). The percentages indicate that, while there is variation between the subsamples, they all independently have a distribution of Airbnb active and inactive zipcodes, which enables us to identify the impact of Airbnb activity in each subsample.

Table 18 shows the results of Equation 1 for all the subsamples. Columns 1, 2, and 3 show the results for the sample of zipcodes with a high proportion of White, Black, and Hispanic residents. Column 4 shows the result for the subsample that have a majority of either Black or Hispanic residents respectively. The results indicate that not all the subsamples are benefitting from the spillover effect of Airbnb. Specifically, the results indicate that,

[19] We use the 2011 American Community Survey from the U.S. Census Bureau to obtain zipcode level data on race/origin.

among the selected demographics, only areas with a high proportion of White residents benefit from the home-sharing platform induced redistributed visitors. Restaurant in areas with a high proportion of Black or Hispanic resident do not appear to benefit from the spillover effect.

One potential rationale for this result relates to the perception of crime and lack of safety often associated with areas with a higher proportion of minorities. NYC data obtained from NYC open data initiative on reported felonies in a zipcode indicates that there is a discrepency in felonies reported in predominately White areas and predomentely Black or Hispanic areas. Specifically, in predominately White areas, there where, on average, 0.08 felonies reported per household. This compares to 0.15 and 0.16 for predominately Black and Hispanic areas respectively. The correlation between reported crime and demographics may by impacting perception which affects the behavior of visitors in terms of visiting local establishments.[20] However, while these results are potentially troublesome, they should be taken with caution when seen as indicative of a racial bias in behavior by Airbnb visitors. The demographics of a location may be affecting the Airbnb visitor behavior due to less auspicious reasons that relate to food preferences. For example, areas with more minority and/or immigrant populations that are not regularly frequented by tourists may have a higher number of specialized/ethnic restaurants. While these type of restaurants may be appealing to a certain type of tourist, other tourists may seek more generic alternatives.

6.2. Heterogeneous Impact of Airbnb due to Restaurant Market Structure

The competitive nature of the restaurants in a locality may also affect the spillover effect of Airbnb on local restaurant performance. On the one hand, more competition may improve the quality and variety of restaurant availability. This would entice visitors of an area to frequent the restaurants in the locality. On the other hand, since these are non-tourist locations, information asymmetry may be problematic in areas with high competition. In other words, it may be difficult for visitors to identify the best restaurant in areas with high competition. This may lead them to frequent restaurants in other areas where it is more clear which restaurants are the popular ones. The impulse to visit the clearly popular restaurants by visitor is exacerbated by the fact that they have a limited amount of restaurants they can visit due to time constraints.

[20] To be clear, it is not our intention to add to the discussion regarding demographics and crime. We are simply drawing a link between perceptions and local behavior of visitors.

To determine the competitive dynamics among the restaurants in a specific zipcode, we calculate the Herfindahl-Hirschman Index (HHI).[21] The market share of each restaurant is calculated using the share of the local Yelp reviews written in 2011. If the local reviews in 2011 are distributed across many restaurants—indicating that there is high competition among the restaurants—then the HHI will be low and indicates a more competitive local area. In contrast, if a few restaurants dominate the majority of the reviews than the competition among the restaurants would be low and the HHI would be large. We use the local Yelp restaurant reviews in 2011 as there is still relatively little Airbnb activity in 2011. Based on the distribution of HHI across the zipcodes we identify each zipcode as having low (below the 33^{rd} percentile), medium (between the 33^{rd} and 66^{th} percentile), or high (greater than the 66^{th} percentile) concentration.

Table 19 shows the results of Equation 1 on the three subsamples of varying local restaurant competition. The results indicate that Airbnb does not have an impact on restaurants in zipcodes that have a low level of restaurant competition (column 3). The impact remains evident in the zipcodes with medium and high competition. The implication is that in areas where a few restaurants dominate the local markets, the benefit from the spillover effects of Airbnb is diminished. Since the restaurants have finite capacity, the dominant restaurants in areas without significant competition do not benefit from the visitors as their capacity is perhaps already reached. The finite capacity issue is likely less problematic in areas with more competitive restaurants as the demand in those areas is distributed among the restaurants. In these areas, restaurants can hire more employees to service the greater demand without necessarily being constrained by capacity.

7. Generalizing the Findings to Other Cities

Thus far, we have identified the impact of Airbnb on restaurant employment in NYC. We have focused on NYC as it is the most active Airbnb city in the United States and is the most visited city overall. To evaluate the extent that our results are generalizable to other cities, we assess the impact of Airbnb intensity on restaurant employment in 5 other cities. Specifically, we obtain Airbnb, Yelp, and local employment data for Austin, TX; Chicago, IL; Los Angeles, CA; Portland, OR; and San Francisco, CA.[22] We aggregate the data at

[21] The HHI index ranges between 0-10,000. It is calculated as the sum of the square of the market share of each restaurant in the zipcode.

[22] We select these cities based on the availibility of Airbnb data from insideairbnb.com.

the zipcode level for each city. We replicate the pre-analysis that was done for NYC by removing the zipcodes where the number of Yelp visitor reviews is significantly higher than other zipcodes in the city. This is to remove those zipcodes that are attractive to visitors regardless of Airbnb availability.

We combine the zipcodes from all the cities and run Equation 1 except that we replace the year fixed effect (δ_t) with a year/city fixed effect. A year/city fixed effect captures city specific events that are time variant such as seasonal festivals. Column 1 of Table 20 presents the results for this analysis and indicates that Airbnb has an impact on restaurant employment beyond NYC. We also conduct Equation 1 on each city individually to evaluate whether the effect holds for all cities. Columns 2-6 of Table 20 present the results. They show that the qualitative nature of the relationship between home sharing and restaurant employment is consistent for all cities. However, the coefficient for Airbnb intensity is not significantly different from zero for Chicago and San Francisco. This indicates that the effect is consistent, although, as expected, city specific heterogeneities drive its magnitude.

We first focus on the result in San Francisco. San Francisco has a significantly smaller land area then the other cities in our sample (San Francisco land area is 46.87 mi^2 compared to the second smallest which is Portland at 145mi^2). While it has a relatively large Airbnb presence, the presence is distributed to all areas. In 2015, the San Francisco zipcode with the least Airbnb intensity had 0.012 Airbnb reviews per household. All other cities in our sample had zipcodes without any Airbnb activity in 2015. Therefore, in San Francisco, Airbnb has distributed to all zipcodes and the small land area means that moving from one location in the city to another is straightforward. Therefore, it is to be expected that San Francisco does not experience within city differences in restaurant employment growth due to the distribution of Airbnb activity.

To further dileanate the drivers of the heterogeneity between cities, we assess the role of demographic differences across cities. In section 6.1 we found that, in NYC, restaurants in areas with majority Black and/or Hispanic residents did not benefit from the spillover effect of home sharing. We replicate the analysis in Table 18 for the zipcodes in the 5 new cities we introduced in this section. Column 1 of Table 21 shows the results of Equation 1 on full sample of zipcodes in the 5 additional cities. Since we are unable to use city-year fixed effects in the subsample analysis due to sample size limitations, we use year fixed effects and we include the effect on the full sample with year fixed effects for comparability.

Column 2,3, and 4 show the results for the subsamples with majority White, Black, and Hispanic residents. The results for the predominately White and Black zipcodes mimic the results in NYC with the effect only present in the predominately White areas. Interestingly, the results for the Hispanic areas indicate that there is a home-sharing spillover effect in this areas.

Since the majority of predominately Black zipcodes in the sample of extended cities are located in Chicago (14/17 zipcodes are in Chicago), this may provide an explanation for the lack of impact in Chicago. The majority of predominately Hispanic zipcodes are located in Los Angeles (25/37). Table 22 presents the results of of Equation 1 on subsamples in Los Angeles. Column 1 presents the results for the predominately White areas and column 2 presents the results for the predominately Hispanic areas. Interestingly, the results indicate that the spillover effect is limited to the Hispanic zipcodes. This indicates that in cities where a specific demographic has significant presence, the spillover effects are experienced by areas with high proportions of that demographic. However, in Chicago, which has the highest proportion of Black residents in our sample (32%), this trend does not continue for areas with majority Black residents.

8. Conclusions and Discussion

As home sharing platforms have gained popularity, they have been met with stiff resistance from local regulators concerned about their negative impact on local communities. Researchers have studied the impact of home sharing platforms on the hotel industry (Zervas et al. 2017), rental prices (Barron et al. 2018), and even its potential for racial discrimination (Edelman et al. 2017). Home sharing platforms are unique in the context of the sharing economy because, on the surface, the negative local externalities (rental prices, housing prices, and negative impact on communities) are directed towards local residents while the positive local externalities are constrained to the Airbnb hosts themselves (Filippas and Horton 2017). In essence, hosts are micro-entrepeuners who are monetizing inventory that would otherwise have remained stagnant (rooms in their homes or whole homes when they are travelling) and visitors have a larger supply of potential short term rental accommodations to choose from. The advantage for the visitor may be realized through a lower fee, a more organic/localized experience, or potentially both. However, the negative economic impact is limited to the residents of the local area.

Regulators in many major cities have focused on these negative aspects to motivate regulatory frameworks designed to limit the impact of home sharing platforms. However, we find that Airbnb, the most prominent home sharing platform in the world, has a positive and salient economic spillover effect on local restaurants. The platforms capacity to redistribute visitors to areas that would otherwise not have had access to these visitor dollars can act as a local economic engine supporting these local restaurants. Our results indicate that if the Airbnb intensity in a neighborhood increases by 2%, then restaurant employment would increase by approximately 3%.

We also find that the impact of Airbnb on restaurant employment is not homogeneously benefiting all areas. Specifically, demographics and market structure have an important role in determining the value extracted by local restaurants from Airbnb activity. Spillover effects of Airbnb on restaurants are diminished in areas with a relatively high number of residents who identify their race as Black. We find a similar result for areas with a relatively high proportion of residents that identify their origin as Hispanic. In contrast, restaurant in areas with a high proportion of White residents benefit from the economic spillover of Airbnb activity. Similar analysis was conducted for 5 additional cities. The results indicate that the lack of spillover for predominately Black areas is consistent for the extended sample. However, interestingly, the result associated with predominately Hispanic areas does not hold. Most of the Hispanic zipcodes in the extended sample are located in Los Angeles. The fact that Los Angeles is approximately 48% Hispanic may change perceptions of potential interactions of people visiting the city. For the market competition heterogeneity analysis, we find that in areas where a few restaurants capture the majority of local Yelp reviews—high concentration areas—the impact of Airbnb on restaurant employment is diminished.

These findings contribute to the growing stream of literature on the direct and indirect impacts of Internet-enabled alternatives on traditional local establishments. The literature on the direct effect has covered the retail market (Brynjolfsson et al. 2009, Forman et al. 2009), local print market (Seamans and Zhu 2013), taxi industry (Cramer and Krueger 2016, Wallsten 2015), and hotel industry (Zervas et al. 2017). We contribute to the growing stream of literature on the spillover effect of these Internet-enabled platforms, with a specific focus on sharing economy platforms (Burtch et al. 2018, Sheppard and Udell 2016, Quattrone et al. 2016, Filippas and Horton 2017, Gong et al. 2018, Barron et al. 2018). Our work is novel in that it focuses on *complimentary* spillover effects. Specifically, we are able to ascertain the affect of an Internet-enabled phenomena—sharing platform induced visitor redistribution—on the actualized economic impact of complimentary services—restaurants.

Our results are also useful for the discussion surrounding the purpose of home-sharing platforms. Airbnb and other home-sharing platforms argue that the majority of their users simply use the platform to augment their income and not as a means of creating investment properties. This would seem to indicate a preference for hosts that share their properties. Our NYC sample focused on areas that are not traditional tourist locations, and descriptive statistics point to the fact that these shared listings are over-represented in our sample. Specifically, in the tourist locations that were removed, 37% of the reviews were attributable to shared listings. This is compared to 60% in our sample of non-tourist locations. As such, our results indicate that areas with a relatively higher proportion of shared listings benefit from the spillover impact of home-sharing visitors. Further analysis regarding the differences in behavior of these two categories of users (private vs. shared) is required to further understand the necessary regulatory actions, if any, that are needed.

While these findings are important to the regulatory discussion around home sharing platforms, they also provide evidence of the potential for the sharing economy to impact the market structure of local restaurants. As more consumers regard home-sharing as a viable alternative, the presence of visitors in localities without a significant hotel presence will grow. This will impact restaurant demand and could prove crucial to local business owners. Importantly, visitors and locals will likely have different preferences and expectations. Since visitors/tourists are generally more willing to spend money at restaurants, their preferences will impact local restaurant outcomes. As restaurant owners react to these changing demand dynamics, the effect will naturally play a role in determining the type of restaurants that make up the local market structure..

Another important aspect of the changing dynamic of visitors is the source and dissemination of information. Airbnb is pushing its hosts to provide information about the local area through guidebooks and recommendations. While Airbnb's main function is to provide a visitor an accommodation, this results in a potential interaction between host and visitor, where the host can give the visitor information on her favorite local establishments. This means that local restaurants may be served by establishing relationships with popular hosts that can serve as a means of advertising. Even Airbnb has recognized the importance of its role as connector of visitors to restaurants and recently purchased the restaurant reservation platform resy.com.[23] Also, these changing dynamics will have an impact on the role of online reviews (Chevalier and Mayzlin 2006). Visitors are likely more dependent on reviews when making restaurant selection. Therefore, the importance of reviews to restaurant performance may be magnified when considering that visitors are becoming more distributed across a city.

[23] https://www.theverge.com/2017/9/20/16338668/airbnb-restaurant-reservation-resy

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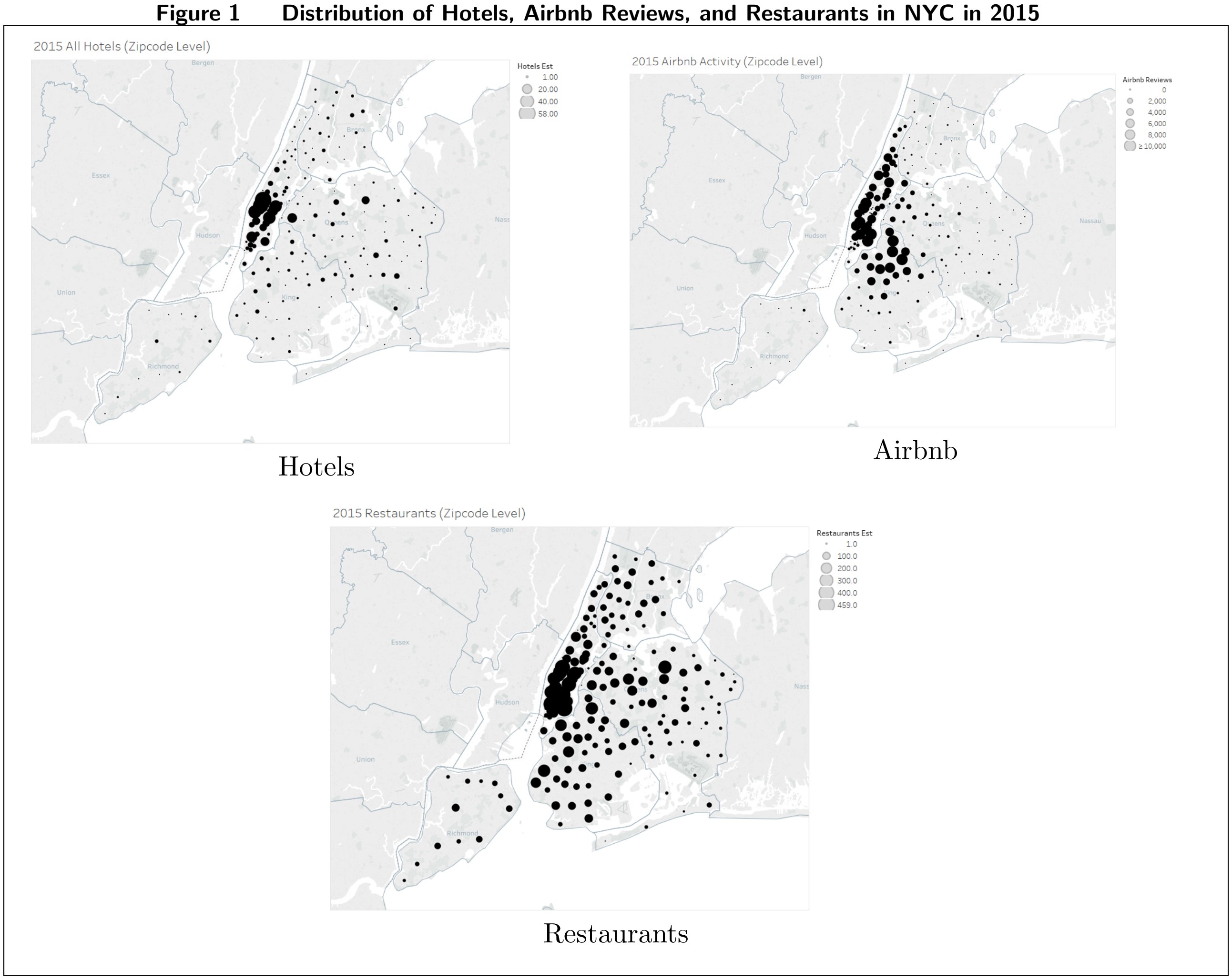
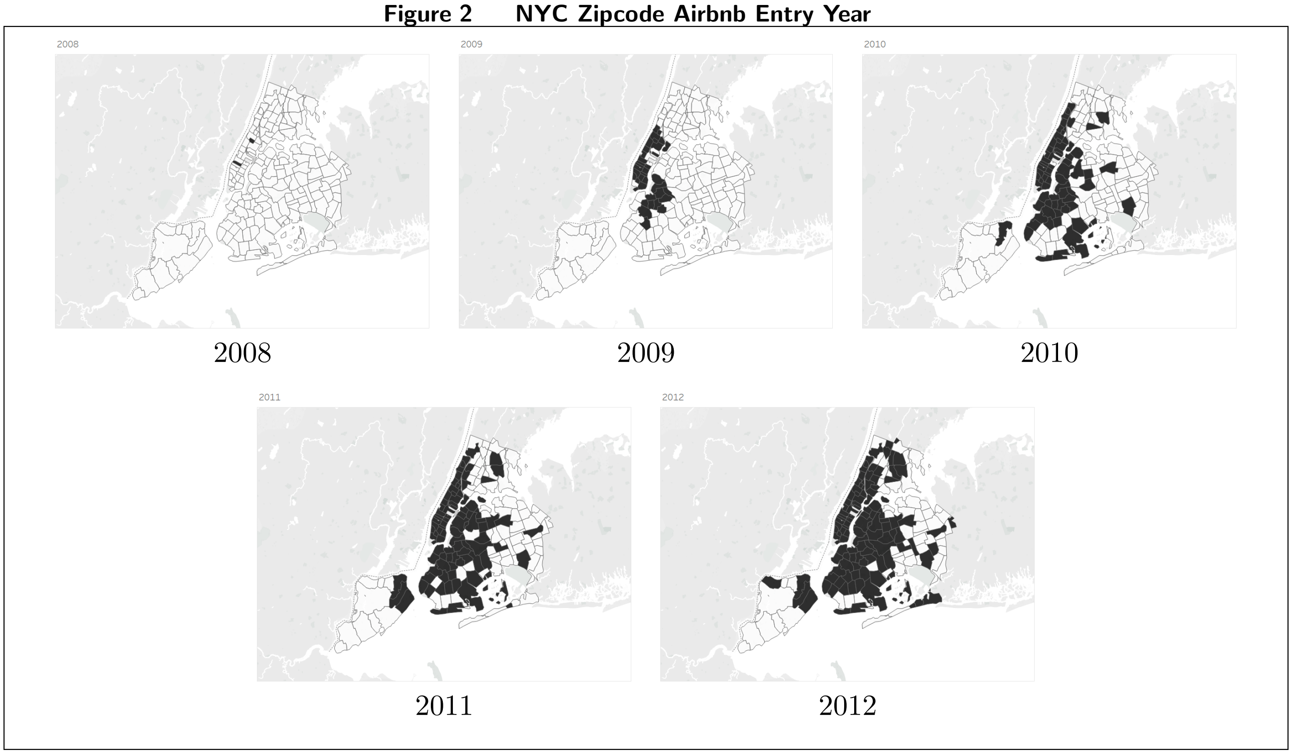
Figures

Figure 1 Distribution of Hotels, Airbnb Reviews, and Restaurants in NYC in 2015



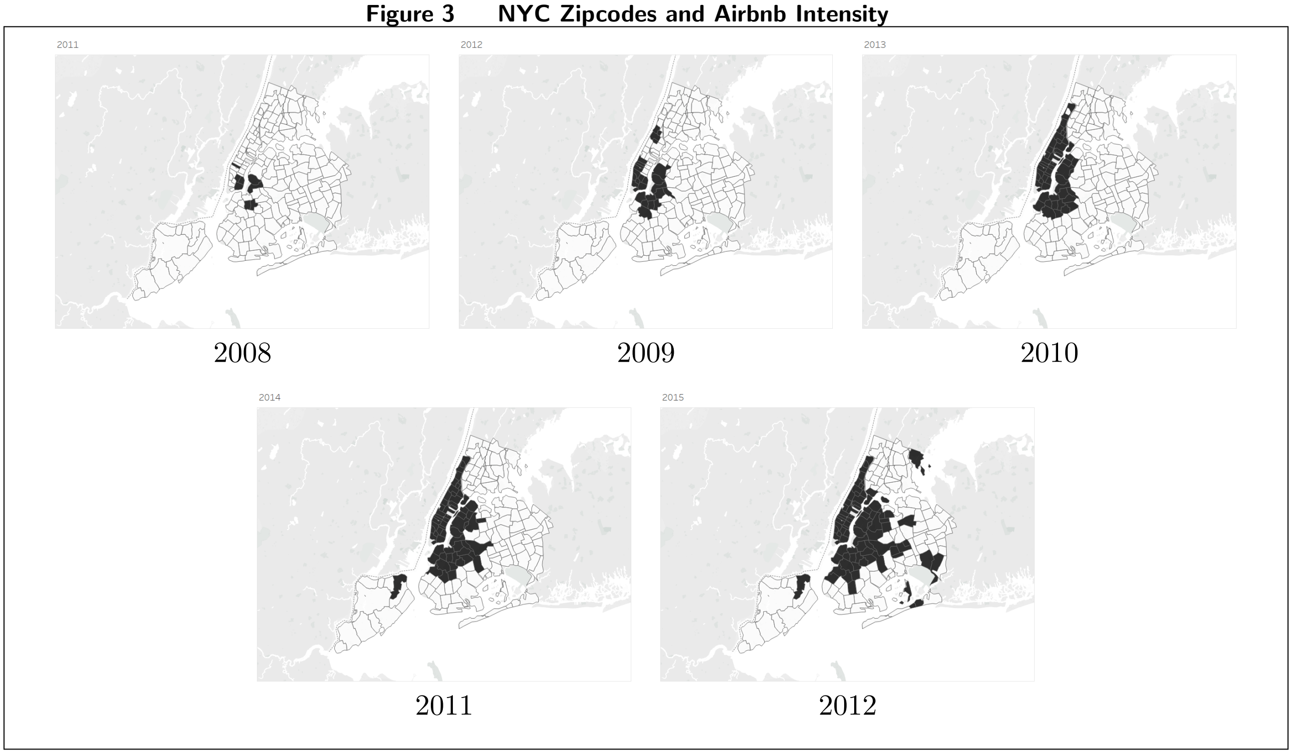
Note: The figure in the upper left corner shows the distribution of hotels across zipcodes in NYC in 2015. The larger circles represent more hotels. The upper right figure shows the distribution of Airbnb activity in 2015. The lower figure shows the distribution of restaurants in 2015.

Figure 2 NYC Zipcode Airbnb Entry Year



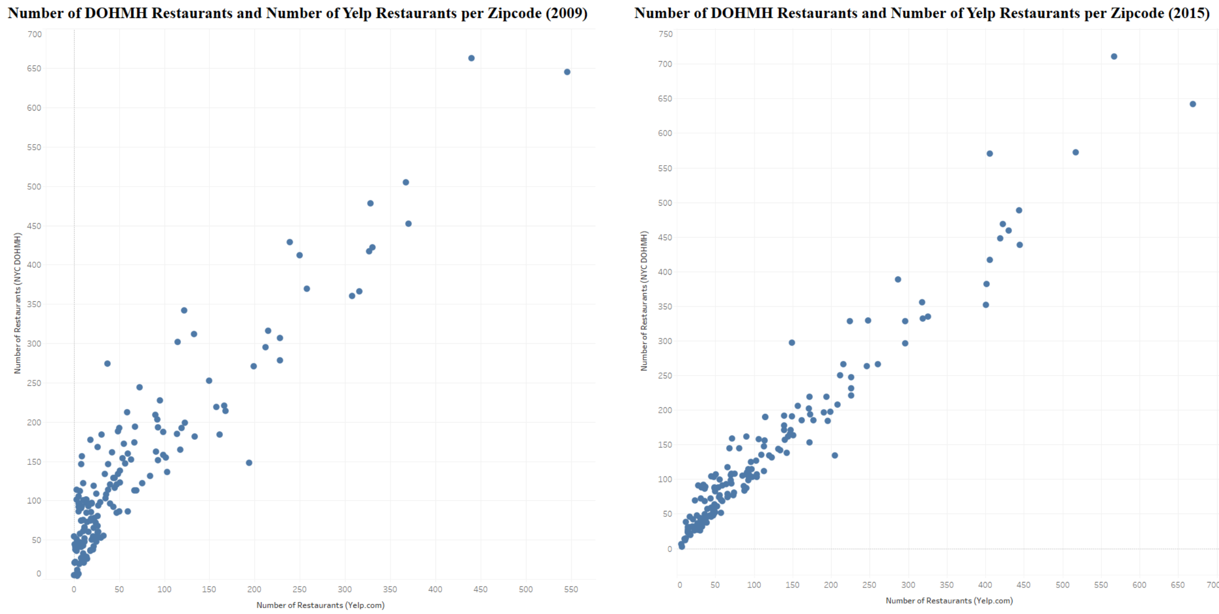
Note: Shows the temporal Airbnb entry for NYC Zipcodes. The zipcodes that are highlighted indicate that an Airbnb review occurred during or before the year.

Figure 3 NYC Zipcodes and Airbnb Intensity



Note: Shows the temporal Airbnb intensity for NYC zipcodes. The zipcodes that are highlighted indicate that the Airbnb reviews per household for that year was greater than 2%.

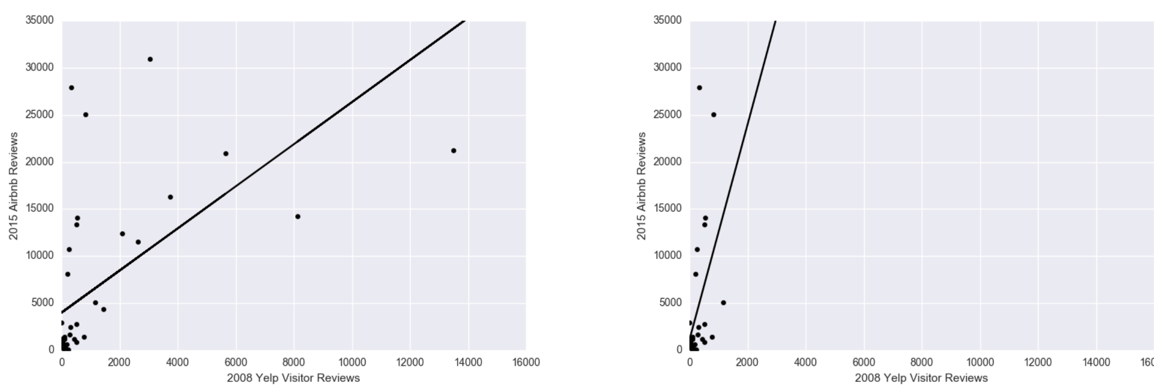
Figure 4 Comparision of Restaurant Count from Yelp and DOHMH



2009 2015

Note: Shows the number of restaurants in a zipcode according to the NYC DOHMH health inspection data against the number of Yelp restaurants active for a year in a specific sample. The left figure is for 2009 and the right figure is for 2015.

Figure 5 2008 Yelp Visitor Reviews / 2015 Airbnb Reviews (Neighborhoods)



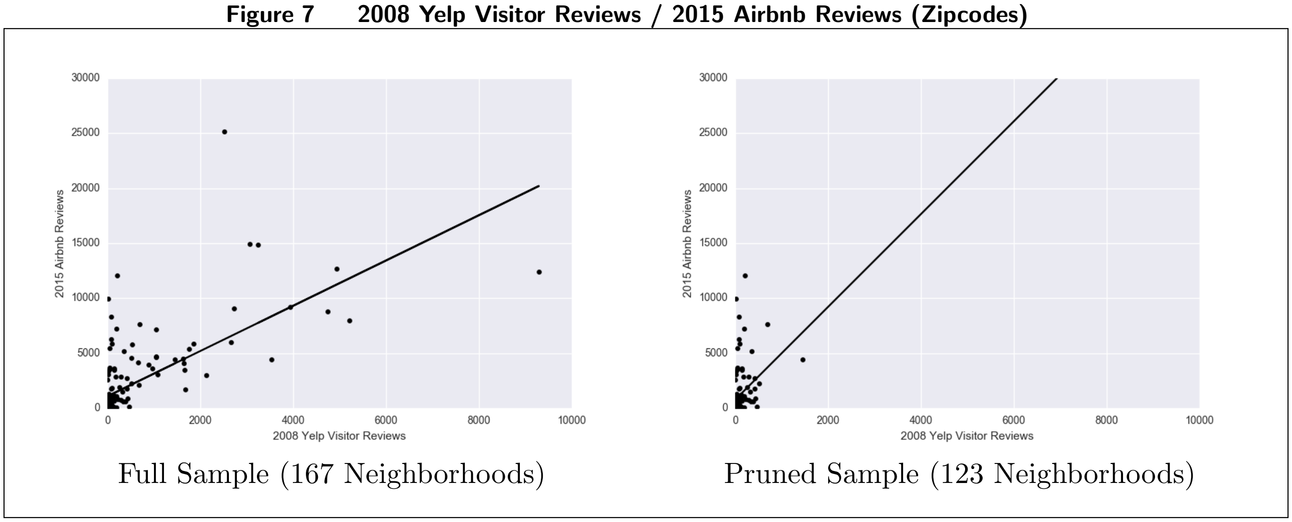
Full Sample (42 Neighborhoods) Pruned Sample (32Neighborhoods)

Note: Plots the number of Yelp Visitor reviews in a neighborhood by the number of Airbnb reviews. Left side is for the full sample of 42 neighborhoods and the right side is for the pruned sample of 32neighborhoods.

Figure 6 Boxplot of 2008 Neighborhood Yelp Visitor Reviews

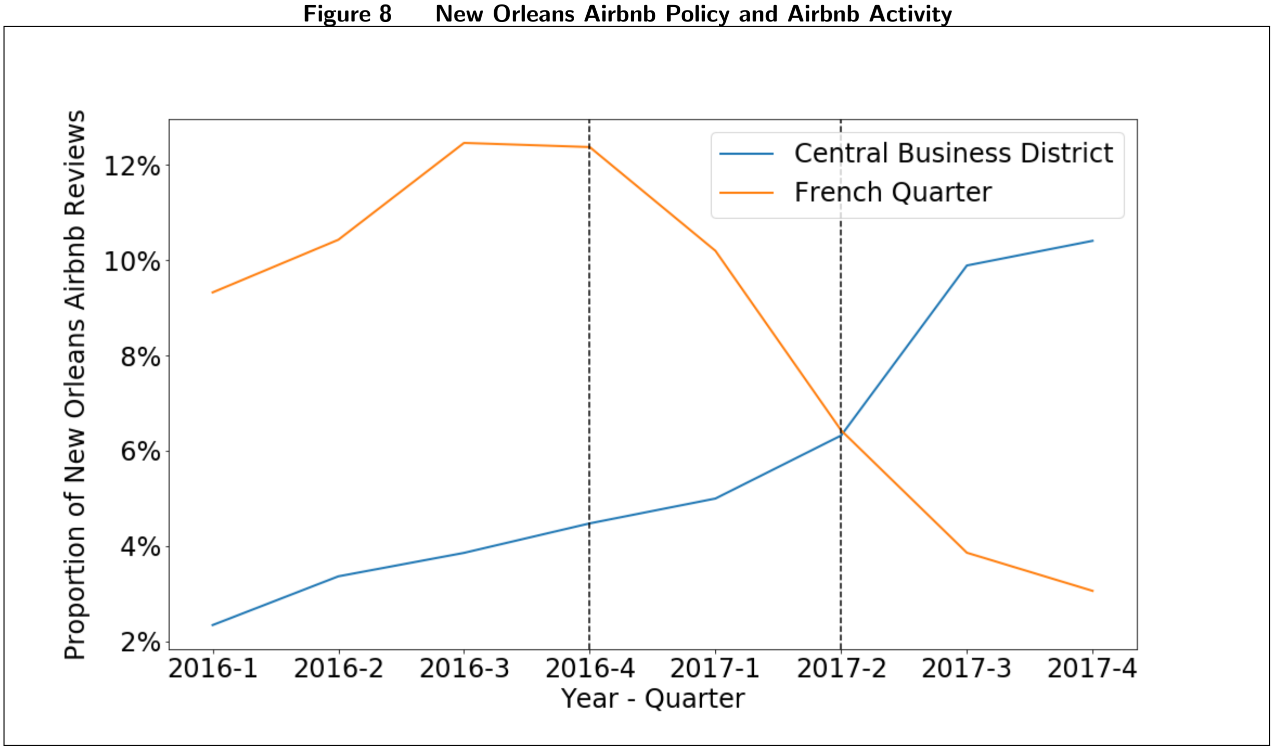
Note: Boxplot of 2008 Yelp Visitor Reviews for the 42 neighborhoods in our sample. The 8 listed neighborhoods are dropped which makes the pruned neighborhood set with 32.

Figure 7 2008 Yelp Visitor Reviews / 2015 Airbnb Reviews (Zipcodes)



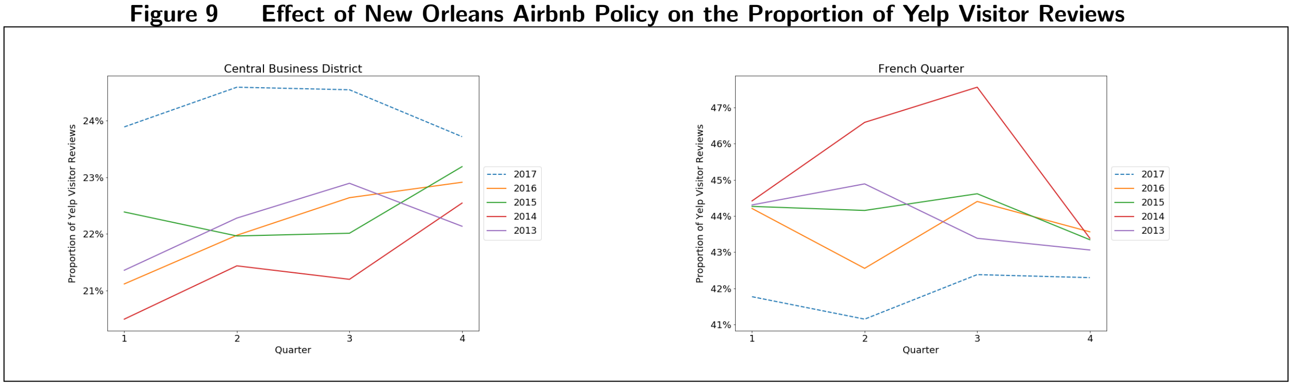
Note: Plots the number of Yelp Visitor reviews in a zipcode by the number of Airbnb reviews. Left side is for the full sample of 167 zipcodes and the right side is for the pruned sample of 123 zipcodes.

Figure 8 New Orleans Airbnb Policy and Airbnb Activity



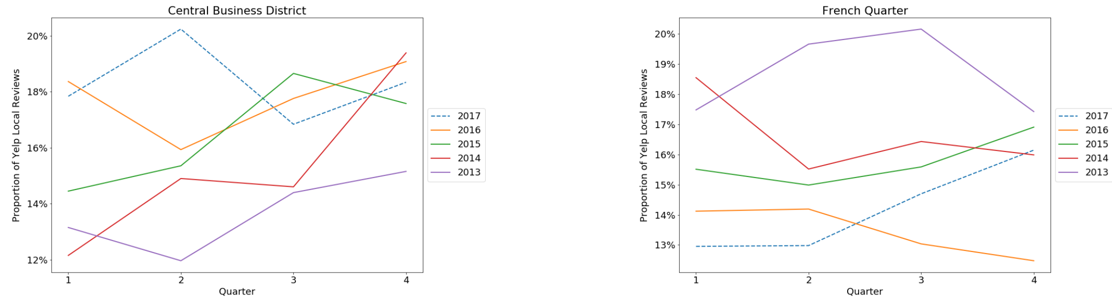
Note: The first dashed line corresponds to the period the New Orleans City Council announced the new Airbnb regulation. The second dashed line is the quarter that the policy was enacted. In the interim, potential hosts were able to register with the city.

Figure 9 Effect of New Orleans Airbnb Policy on the Proportion of Yelp Visitor Reviews



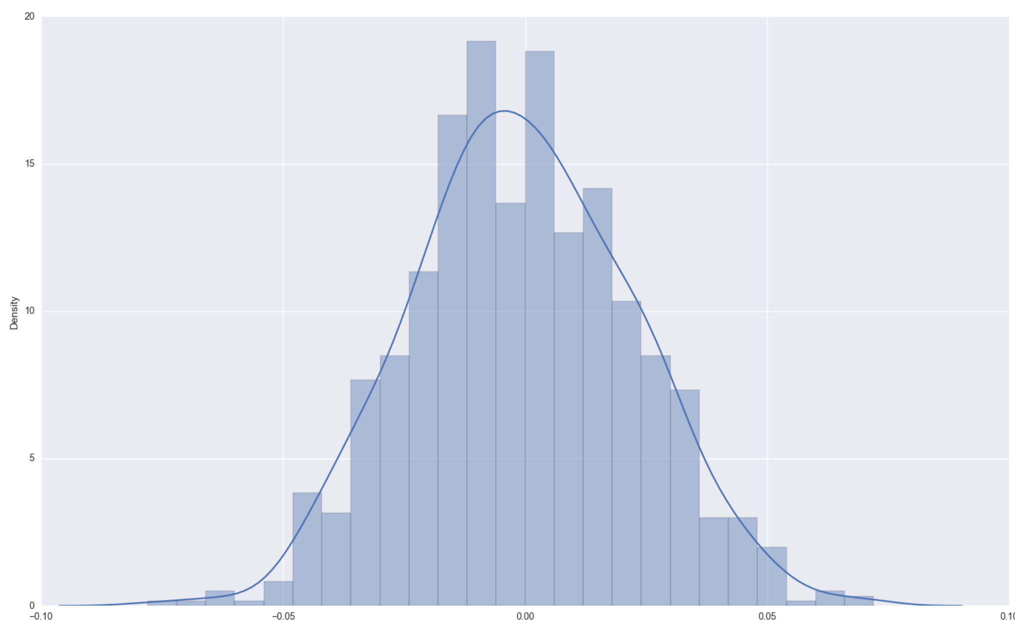
Note: Dashed line represents 2017 which is the year after the New Orleans Airbnb Policy was implemented.

Figure 10 Effect of New Orleans Airbnb Policy on the Proportion of Yelp Local Reviews



Note: Dashed line represents 2017 which is the year after the New Orleans Airbnb Policy was implemented.

Figure 11 Distribution of Airbnb Binary Coefficient for Randomly Assigned Treatments



Note: Distribution of 1,000 iterations of Equation 1 based on a randomly assigned binary Airbnb treatment indicator.

Tables

Table 1 Neighborhood Summary Statistics

Neighborhood	County	Housing Units	Median Income	% Black	% Hispanic	# of Restaurants	# of Retail Establishments
Bronx Park and Fordham	Bronx	91,135	31,369	32	58	295	792
Central Bronx	Bronx	72,682	24,562	35	68	168	569
High Bridge and Morrisania	Bronx	74,938	24,979	42	61	233	588
Hunts Point and Mott Haven	Bronx	48,361	21,129	34	72	194	589
Kingsbridge and Riverdale	Bronx	39,770	57,792	15	41	145	190
Northeast Bronx	Bronx	72,946	49,277	63	24	193	417
Southeast Bronx	Bronx	116,039	45,136	26	49	399	812
Borough Park	Brooklyn	113,772	43,622	5	12	384	1,531
Bushwick and Williamsburg	Brooklyn	81,107	34,184	35	50	265	656
Canarsie and Flatlands	Brooklyn	74,424	61,008	64	9	221	569
Central Brooklyn	Brooklyn	140,723	40,178	74	12	424	868
East New York and New Lots	Brooklyn	67,906	34,140	59	37	178	510
Flatbush	Brooklyn	116,659	45,339	76	10	332	884
Greenpoint	Brooklyn	55,159	50,326	4	22	436	758
Northwest Brooklyn	Brooklyn	109,726	79,866	17	18	985	1,241
Southern Brooklyn	Brooklyn	115,891	42,156	7	10	465	1,283
Southwest Brooklyn	Brooklyn	81,549	51,876	2	13	440	810
Sunset Park	Brooklyn	41,857	38,790	4	43	339	794
Central Harlem	Manhattan	76,720	36,641	62	22	218	371
Chelsea and Clinton	Manhattan	96,755	84,692	7	15	1,911	2,936
East Harlem	Manhattan	45,510	29,728	34	49	207	392
Gramercy Park and Murray Hill	Manhattan	88,126	102,816	4	7	1,283	1,549
Greenwich Village and Soho	Manhattan	49,231	87,227	3	5	1,272	1,916
Inwood and Washington Heights	Manhattan	97,606	39,162	24	66	357	858
Lower East Side	Manhattan	97,879	59,896	7	19	1,420	1,212
Lower Manhattan	Manhattan	28,368	65,934	7	16	520	491
Upper East Side	Manhattan	97,786	101,860	4	7	527	943
Upper West Side	Manhattan	124,583	92,508	10	14	551	678
Central Queens	Queens	36,326	57,019	8	15	139	273
Jamaica	Queens	100,273	56,064	57	18	358	863
North Queens	Queens	99,557	57,630	3	16	731	1,155
Northeast Queens	Queens	35,455	77,135	3	11	198	230
Northwest Queens	Queens	92,529	52,016	6	29	744	963
Rockaways	Queens	45,518	50,404	41	21	106	207
Southeast Queens	Queens	63,949	76,833	60	11	181	360
Southwest Queens	Queens	91,163	59,085	13	33	387	762
West Central Queens	Queens	106,686	61,054	3	25	452	947
West Queens	Queens	159,151	49,080	6	48	884	1,600
Mid-Island	Staten	32,529	79,820	4	13	139	332
Port Richmond	Staten	25,143	56,464	30	34	127	245
South Shore	Staten	70,672	84,661	2	10	272	425
Stapleton and St. George	Staten	48,386	57,740	20	21	177	274

Note: Summary statistics for the 42 NYC neighborhoods in our sample. Data obtained from the U.S. Census Bureau from the 2012 American Community Survey as well as Business Pattern Data.

Table 2 Airbnb Reviews Summary Statistics

		2007	2008	2009	2010	2011	2012	2013	2014	2015
Airbnb Reviews	Total	0	2	705	3,903	13,333	33,639	79,205	186,727	342,947
Neighborhood Level	Median	0	0	0	11	43	147	331	725	1,557
	Max	0	1	127	713	2,510	5,235	12,044	25,481	42,216
	Min	0	0	0	0	0	0	0	17	84
	St. Dev	0	0	32	160	538	1,240	2,840	6,453	11,199
Zipcode Level	Median	0	0	0	0	2	19	49	138	348
	Max	0	1	73	382	1,091	2,766	6,322	15,315	25,173
	Min	0	0	0	0	0	0	0	0	0
	St. Dev	0	0	11	53	170	389	890	2,055	3,541
	Airbnb Reviews for Shared Listings	0	2	294	1,724	5,939	14,306	33,802	81,827	155,785
	Airbnb Reviews for Private Listings	0	0	411	2,179	7,394	19,333	45,403	104,900	187,162
	Ratio Shared/ Total Reviews		100.0%	41.7%	44.2%	44.5%	42.5%	42.7%	43.8%	45.4%
	Ratio Private/ Total Reviews		0.0%	58.3%	55.8%	55.5%	57.5%	57.3%	56.2%	54.6%

Note: Summary statistics for the Airbnb reviews collected.

Table 3 Yelp Reviews Summary Statistics

		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Yelp Active Restaurants	Total	1,488	4,216	6,933	9,185	11,228	13,176	14,962	16,441	17,805	18,968	20,064
Neighborhood Level	Median	2	15	50	101	137	166	211	249	286	307	353
	Max	319	778	1,175	1,378	1,572	1,716	1,845	1,950	2,096	2,150	2,205
	Min	0	0	0	6	19	23	33	41	63	76	93
	St. Dev	77	189	266	304	336	363	385	403	425	432	437
Zipcode Level	Median	0	3	10	17	26	35	41	50	56	67	72
	Max	173	350	459	510	546	582	591	612	635	668	669
	Min	0	0	0	0	0	0	1	4	6	5	6
	St. Dev	23	54	74	85	93	101	106	110	116	119	120
Yelp Visitor Reviews	Total	1,039	5,740	17,373	30,862	46,862	66,216	84,071	89,162	100,044	122,272	148,394
Neighborhood Level	Median	1	10	23	86	144	176	253	272	315	365	511
	Max	259	1,272	3,855	6,460	9,961	14,718	19,788	22,030	25,930	34,281	42,864
	Min	0	0	0	1	2	5	7	12	27	16	23
	St. Dev	58	322	946	1,632	2,428	3,457	4,378	4,648	5,233	6,495	7,909
Zipcode Level	Median	0	1	5	10	18	26	36	38	53	74	108
	Max	128	758	2,031	3,657	5,272	7,310	8,446	8,440	8,818	11,759	14,755
	Min	0	0	0	0	0	0	0	0	0	0	1
	St. Dev	18	98	280	487	717	1,006	1,258	1,319	1,456	1,791	2,151
Yelp Local Reviews	Total	1,305	6,636	17,523	33,633	57,228	83,730	115,140	128,982	149,666	191,959	231,996
Neighborhood Level	Median	1	9	50	125	282	438	667	779	972	1,427	2,128
	Max	334	1,454	3,672	6,917	11,380	15,605	18,613	19,459	22,159	27,201	31,730
	Min	0	0	0	1	7	10	19	38	44	93	158
	St. Dev	75	363	872	1,603	2,614	3,646	4,716	5,068	5,667	6,799	7,722
Zipcode Level	Median	0	2	8	16	34	63	100	123	169	269	377
	Max	195	919	2,176	4,061	6,748	8,635	10,348	10,996	12,387	14,775	16,044
	Min	0	0	0	0	0	0	0	0	0	4	7
	St. Dev	23	111	265	488	802	1,089	1,401	1,502	1,681	2,010	2,266

Note: Summary statistics for the Airbnb reviews collected.

Table 4 Neighborhood Dropped Due to High Tourist Attractiveness Prior To Airbnb

Neighborhood	County	Yelp Visitor Reviews (2008)	% Yelp Visitor Reviews (2008)	Yelp Visitor Reviews (2015)	% Yelp Visitor Reviews (2015)	Airbnb Reviews (2015)	% Airbnb Reviews (2015)
Greenpoint	Brooklyn	1,062	3.4%	4,176	2.8%	30,977	9.0%
Northwest Brooklyn	Brooklyn	1,733	5.6%	6,281	4.2%	20,915	6.1%
Chelsea and Clinton	Manhattan	6,460	20.9%	42,864	28.9%	40,413	11.8%
Gramercy Park and Murray Hill	Manhattan	3,356	10.9%	17,458	11.8%	14,206	4.1%
Greenwich Village and Soho	Manhattan	5,904	19.1%	21,911	14.8%	21,219	6.2%
Lower East Side	Manhattan	6,163	20.0%	19,146	12.9%	42,216	12.3%
Upper East Side	Manhattan	1,094	3.5%	3,889	2.6%	11,510	3.4%
Upper West Side	Manhattan	1,562	5.1%	6,150	4.1%	16,333	4.8%

Note: This table shows the 2008 Yelp visitor reviews for the 8 dropped neighborhoods.

Table 5 Airbnb Neighborhood Level Impact on Restaurant Employment

	(1)	(2)	(3)	(4)	(5)
Dep. Variable:	log(Restaurant Employment)	log(Restaurant Employment)	log(Restaurant Employment)	log(Restaurant Employment)	log(Restaurant Employment)
Airbnb Reviews per Household	**0.791*** **	**1.736*** **	**1.721*** **	**1.516*** **	**1.588*** **
	(0.252)	(0.526)	(0.512)	(0.433)	(0.414)
Local Rest. Popularity	-0.027		0.324	0.389	0.373
	(0.039)		(0.435)	(0.331)	(0.357)
log(Active Restaurants)	0.030*		0.051**	0.038**	0.041*
	(0.015)		(0.019)	(0.018)	(0.020)
log(Hotel Employees)	0.057***			0.055***	0.056***
	(0.014)			(0.015)	(0.016)
log(Retail Employees)	0.436***			0.316*	0.125
	(0.128)			(0.171)	(0.157)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Constant	3.753***	7.370***	7.312***	4.509***	6.091***
	(1.103)	(0.021)	(0.028)	(1.422)	(1.295)
Observations	462	352	352	352	264
R-squared	0.786	0.728	0.739	0.784	0.816
Number of neighborhoods	42	32	32	32	24

Note: This table presents the results of Equation 1, which evaluates the impact of Airbnb intensity (Airbnb Reviews per Household) on Restaurant Employment at the neighborhood aggregation level. Column 1 includes the full sample of unpruned neighborhoods. Column 2-4 show the results for the pruned sample of neighborhoods. Column 5 shows the results based on the manual neighborhood matching technique.

Table 6 Neighborhood Manual Matching

Neighborhood	County	Yelp Visitor Reviews (2008)	% Airbnb Reviews per Household (2015)	Match ID
Central Bronx	Bronx	1	0.49%	1
Southeast Queens	Queens	2	0.73%	0
East New York and New Lots	Brooklyn	2	4.18%	1
Northeast Bronx	Bronx	4	0.63%	2
Hunts Point and Mott Haven	Bronx	5	1.29%	2
High Bridge and Morrisania	Bronx	7	1.05%	0
Canarsie and Flatlands	Brooklyn	11	0.97%	0
Port Richmond	Staten	11	0.63%	0
Mid-Island	Staten	15	0.47%	3
Jamaica	Queens	17	1.28%	3
South Shore	Staten	22	0.32%	4
Stapleton and St. George	Staten	24	2.40%	4
Southwest Queens	Queens	31	1.55%	0
Rockaways	Queens	34	1.86%	5
Central Queens	Queens	37	0.55%	5
Bronx Park and Fordham	Bronx	41	0.49%	0
Southeast Bronx	Bronx	43	0.55%	0
Kingsbridge and Riverdale	Bronx	43	0.85%	0
Northeast Queens	Queens	57	0.24%	6
Flatbush	Brooklyn	62	6.92%	6
Borough Park	Brooklyn	80	2.20%	7
Sunset Park	Brooklyn	92	4.09%	8
East Harlem	Manhattan	96	22.92%	7
Southwest Brooklyn	Brooklyn	104	1.08%	8
Southern Brooklyn	Brooklyn	115	1.00%	9
Bushwick and Williamsburg	Brooklyn	120	33.65%	9
West Central Queens	Queens	123	2.58%	10
Inwood and Washington Heights	Manhattan	127	13.60%	10
Central Harlem	Manhattan	226	18.48%	11
North Queens	Queens	237	1.43%	11
Central Brooklyn	Brooklyn	272	17.39%	12
West Queens	Queens	308	3.16%	12
Lower Manhattan	Manhattan	511	13.85%	0
Northwest Queens	Queens	648	13.14%	0

Note: This table displays the manual matching results for the neighborhood analysis. The greyed out neighborhoods indicate neighborhoods that were not match and were therefore discarded. Neighborhoods with the same match ID are matched based on 2008 Yelp Visitor Reviews and that they have substantial differences in 2015 Airbnb intensity.

Table 7 Airbnb Zipcode Level Impact on Restaurant Employment

	(1)	(2)	(3)	(4)	(5)
Dep. Variable:	log(Restaurant Employment)	log(Restaurant Employment)	log(Restaurant Employment)	log(Restaurant Employment)	log(Restaurant Employment)
Airbnb Reviews per Household	**0.841*****	**1.827*****	**1.559*****	**1.455*****	**1.463*****
	(0.176)	(0.374)	(0.338)	(0.350)	(0.391)
Local Rest. Popularity	0.022		1.425***	1.459***	2.221***
	(0.118)		(0.441)	(0.426)	(0.529)
log(Active Restaurants)	0.027*		0.032**	0.026*	0.015
	(0.014)		(0.014)	(0.014)	(0.021)
log(Hotel Employees)	0.025**			0.022*	-0.010
	(0.010)			(0.012)	(0.014)
log(Retail Employees)	0.278***			0.124	0.036
	(0.069)			(0.077)	(0.111)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Constant	4.175***	5.990***	5.966***	5.080***	5.752***
	(0.480)	(0.017)	(0.017)	(0.534)	(0.773)
Observations	1,837	1,353	1,353	1,353	638
R-squared	0.515	0.508	0.520	0.529	0.620
Number of zipcodes	167	123	123	123	58

Note: This table presents the results of Equation 1, which evaluates the impact of Airbnb intensity (Airbnb Reviews per Household) on Restaurant Employment at the zipcode aggregation level. Column 1 includes the full sample of unpruned zipcodes. Columns 2-4 show the results for the pruned sample of zipcodes. Column 5 shows the results after matching the data using nearest neighbor matching based on Propensity Score and removing unmatched zipcodes.

Table 8 Matching Sensitivity Analysis for Airbnb Treatment (Dep. Var.: Restaurant Employment)

		Lower Treatment Percentile				
		$35^{th}\%$	$40^{th}\%$	$45^{th}\%$	$50^{th}\%$	$55^{th}\%$
Upper	$70^{th}\%$	1.463***	1.454***	1.354***	1.419***	1.459***
Treatment	$65^{th}\%$	1.146***	1.352***	1.431***	1.375***	1.323***
Percentile	$60^{th}\%$	1.419***	1.543***	1.451***	1.447***	1.504***

Note: The table presents a sensitivity analysis of the treatment and control criteria discussed in section 3.3.1. The coefficient for Airbnb reviews per household from Equation 1 is presented for different specification of treatment and control. For example, the upper left coefficient refers to the case where treated zipcodes are those where the Airbnb per household ratio in 2015 is greater than the 70^{th} percentile for all zipcodes and less than the 35^{th} percentile for untreated zipcodes.

Table 9 Airbnb Impact on Proportion of NYC Visitor Yelp Reviews

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable:	Prop. NYC Yelp Visitor Reviews	Prop. NYC Yelp Visitor Reviews	Prop. NYC Yelp Local Reviews	Prop. NYC Yelp Visitor Reviews	Prop. NYC Yelp Visitor Reviews	Prop. NYC Yelp Local Reviews
Airbnb Reviews	**0.705*** **	**0.780*** **	**-0.095**	**0.199** **	**0.225*** **	**-0.144* **
per Household	(0.233)	(0.235)	(0.067)	(0.078)	(0.069)	(0.086)
Local Rest.	2.917***	3.078***	13.211***	1.758***	1.555***	6.049***
Popularity	(0.629)	(0.656)	(0.143)	(0.564)	(0.223)	(0.225)
log(Active Restaurants)	0.024	0.023	0.020**	0.009*	0.020***	0.021***
	(0.023)	(0.024)	(0.008)	(0.005)	(0.007)	(0.006)
log(Hotel Employees)	0.007	0.006	-0.003	0.003	-0.001	0.004
	(0.012)	(0.013)	(0.004)	(0.002)	(0.004)	(0.003)
log(Retail Employees)	-0.092	-0.125	0.005	-0.007	-0.007	-0.009
	(0.063)	(0.084)	(0.026)	(0.010)	(0.015)	(0.018)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.818	1.138	-0.022	0.091	0.071	0.076
	(0.541)	(0.729)	(0.232)	(0.071)	(0.100)	(0.131)
Observations	288	216	216	1,107	522	522
R-squared	0.712	0.716	0.996	0.406	0.594	0.948
Number of neighborhoods	32	24	24	123	58	58

Note: This table presents the results of Equation 2, which evaluates the impact of Airbnb intensity (Airbnb Reviews per Household) on the proportion of NYC Yelp visitor reviews captured by an area. Columns 1-3 are at the neighborhood level of aggregation. Column 1 is for the pruned sample of zipcodes, column 2 is for the matched sample of neighborhoods, and column 3 conducts the test which replaces visitor reviews with local reviews. Columns 4-6 are for the zipcode level and provide the analogous results.

Table 10 Matching Sensitivity Analysis for Airbnb Treatment (Dep. Var.: Proportion Yelp Visitor Reviews)

		Lower Treatment Percentile				
		$35^{th}\%$	$40^{th}\%$	$45^{th}\%$	$50^{th}\%$	$55^{th}\%$
Upper	$70^{th}\%$	0.225***	0.224***	0.209***	0.224***	0.218***
Treatment	$65^{th}\%$	0.249***	0.251***	0.194***	0.196***	0.189***
Percentile	$60^{th}\%$	0.270***	0.220***	0.202***	0.198***	0.199***

Note: The table presents a sensitivity analysis of the treatment and control criteria discussed in section 3.3.1. The coefficient for Airbnb reviews per household from Equation 2 is presented for different specification of treatment and control.

Table 11 Matching Sensitivity Analysis for Airbnb Treatment (Dep. Var.: Prop. Yelp Local Reviews)

		Lower Treatment Percentile				
		$35^{th}\%$	$40^{th}\%$	$45^{th}\%$	$50^{th}\%$	$55^{th}\%$
Upper	$70^{th}\%$	-0.144*	-0.144*	-0.149*	-0.125	-0.160*
Treatment	$65^{th}\%$	-0.046	-0.077	-0.130	-0.133*	-0.132
Percentile	$60^{th}\%$	-0.034	-0.143	-0.149*	-0.165*	-0.165*

Note: The table presents a sensitivity analysis of the treatment and control criteria discussed in section 3.3.1. The coefficient for Airbnb reviews per household from Equation 3 is presented for different specification of treatment and control.

Table 12 Robustness Check: Alternative Definitions for Airbnb Intensity

Dep. Variable:	(1) log(Airbnb Reviews)	(2) Airbnb Measure (1)	(3) Airbnb Measure (2)	(4) Airbnb Measure (3)
Airbnb Intensity Measure	**0.018***	**0.014****	**0.059**	**0.097***
	(0.009)	(0.006)	(0.035)	(0.049)
Local Rest. Popularity	0.526	0.490	0.579	0.564
	(0.386)	(0.348)	(0.382)	(0.370)
log(Active Restaurants)	0.036*	0.040**	0.037*	0.039*
	(0.019)	(0.019)	(0.020)	(0.020)
log(Hotel Employees)	0.055***	0.053***	0.054***	0.053***
	(0.014)	(0.015)	(0.014)	(0.015)
log(Retail Employees)	0.328**	0.339*	0.352**	0.344**
	(0.160)	(0.167)	(0.160)	(0.165)
Year Fixed Effects	Yes	Yes	Yes	Yes
Constant	4.412***	4.322***	4.205***	4.271***
	(1.341)	(1.395)	(1.343)	(1.381)
Observations	352	352	352	352
R-squared	0.759	0.765	0.755	0.760
Number of neighborhoods	32	32	32	32

Note: This table presents robustness checks for the definition of Airbnb intensity in Equation 1, which evaluates the impact of Airbnb intensity on Restaurant Employment at the neighborhood level. Column 1 presents the results when Airbnb intensity is measured by log(Airbnb Reviews). Column 2 shows the results for a definition of Airbnb that is zero if the ratio of Airbnb to households is less than 2%, otherwise it is log(Airbnb Reviews). Column 3 shows the results for a definition where Airbnb Intensity is 0 if the Airbnb per household in a period is less than 1%, otherwise it is 1. Column 4 is the same as column 3 except the threshold of Airbnb reviews per household is 2%.

Table 13 Robustness Check: Alternative Definitions for Airbnb Intensity (Zipcode Level)

	(1)	(2)	(3)	(4)
Dep. Variable:	log(Airbnb Reviews)	Airbnb Measure (1)	Airbnb Measure (2)	Airbnb Measure (3)
Airbnb Intensity Measure	**0.020****	**0.019*****	**0.092*****	**0.110*****
	(0.008)	(0.005)	(0.028)	(0.034)
Local Rest. Popularity	1.755***	1.665***	1.823***	1.796***
	(0.519)	(0.473)	(0.521)	(0.502)
log(Active Restaurants)	0.023	0.027*	0.026*	0.027*
	(0.015)	(0.015)	(0.015)	(0.015)
log(Hotel Employees)	0.023*	0.023*	0.023*	0.024*
	(0.012)	(0.012)	(0.012)	(0.012)
log(Retail Employees)	0.132*	0.139*	0.141*	0.144*
	(0.078)	(0.078)	(0.078)	(0.078)
Year Fixed Effects	Yes	Yes	Yes	Yes
Constant	5.025***	4.974***	4.963***	4.941***
	(0.540)	(0.542)	(0.543)	(0.543)
Observations	1,353	1,353	1,353	1,353
R-squared	0.514	0.520	0.514	0.516
Number of zipcodes	123	123	123	123

Note: This table presents robustness checks for the definition of Airbnb intensity in Equation 1, which evaluates the impact of Airbnb intensity on Restaurant Employment at the zipcode level. Column 1 presents the results when Airbnb intensity is measured by log(Airbnb Reviews). Column 2 shows the results for a definition of Airbnb that is zero if the ratio of Airbnb to households is less than 2%, otherwise it is log(Airbnb Reviews). Column 3 shows the results for a definition where Airbnb Intensity is 0 if the Airbnb per household in a period is less than 1%, otherwise it is 1. Column 4 is the same as column 3 except the threshold of Airbnb reviews per household is 2%.

Table 14 Robustness Checks: Alternative Definitions for Restaurant Employment

Dep. Variable:	(1) log(Restaurant Employment)	(2) log(Restaurant Employment)
Airbnb Reviews per Household	**1.298*** **	**1.522*** **
	(0.412)	(0.454)
Local Rest. Popularity	0.361	0.360
	(0.328)	(0.334)
log(Active Restaurants)	0.048**	0.045**
	(0.019)	(0.019)
log(Hotel Employees)	0.049***	0.050***
	(0.013)	(0.015)
log(Retail Employees)	0.259	0.308
	(0.157)	(0.185)
Year Fixed Effects	Yes	Yes
Constant	4.858***	4.481***
	(1.304)	(1.542)
Observations	352	352
R-squared	0.742	0.744
Number of neighborhoods	32	32

Note: This table presents the results of specification 1 except that the dependent variable definition is adjusted. In column 1 restaurant employment includes only full-service restaurants and limited services restaurants. In column 2 drinking places are added as well.

Table 15 Robustness Check: Matching (using Mahalanobis distance) Sensitivity Analysis for Airbnb Treatment (Dep. Var.: Restaurant Employment)

		Lower Treatment Percentile				
		35^{th}%	40^{th}%	45^{th}%	50^{th}%	55^{th}%
Upper	70^{th}%	1.344***	1.426***	1.334***	1.390***	1.339***
Treatment	65^{th}%	1.391***	1.399***	1.396***	1.402***	1.289***
Percentile	60^{th}%	1.387***	1.418***	1.409***	1.356***	1.377***

Note: The table presents a sensitivity analysis of the treatment and control criteria for the Mahalanobis matching method discussed in section 3.3.1. The coefficient for Airbnb reviews per household from Equation 1 is presented for different specification of treatment and control. For example, the upper left coefficient refers to the case where treated zipcodes are those where the Airbnb per household ratio in 2015 is greater than the 70^{th} percentile for all zipcodes and less than the 35^{th} percentile for untreated zipcodes.

Table 16 Robustness Check: Matching (using CEM) Sensitivity Analysis for Airbnb Treatment (Dep. Var.: Restaurant Employment)

		Lower Treatment Percentile				
		$35^{th}\%$	$40^{th}\%$	$45^{th}\%$	$50^{th}\%$	$55^{th}\%$
Upper	$70^{th}\%$	2.260***	2.244***	1.776***	1.596***	1.500***
Treatment	$65^{th}\%$	2.216***	2.205***	1.736***	1.565***	1.478***
Percentile	$60^{th}\%$	2.185***	2.183***	1.672***	1.467***	1.402***

Note: The table presents a sensitivity analysis of the treatment and control criteria for the CEM matching method discussed in section 3.3.1. The coefficient for Airbnb reviews per household from Equation 1 is presented for different specification of treatment and control. For example, the upper left coefficient refers to the case where treated zipcodes are those where the Airbnb per household ratio in 2015 is greater than the 70^{th} percentile for all zipcodes and less than the 35^{th} percentile for untreated zipcodes.

Table 17 Demographic Statistics

Demographic	Zipcode Average	Zipcode Median	Zipcode 75^{th} Percentile	Airbnb Intensity $< 2\%$	Airbnb Intensity $\geq 2\%$ Average
White	43.8%	43.1%	62.2%	68.8%	31.2%
Black or African American	27.5%	17.1%	40.0%	44.0%	56.0%
Hispanic	31.1%	24.7%	45.2%	53.8%	46.2%

Note: This table presents the summary statistics for the distribution of demographics across zipcodes. The right hand side of the table shows the distribution of Airbnb intensity among zipcodes with a majority of a specific demographic (greater than 50%).

Table 18 Heterogeneity of Airbnb Impact (Subsample by Demographics)

	(1)	(2)	(3)	(4)
Dep. Variable: log(Restaurant Employment)	High Ratio of White Residents	High Ratio of Black Residents	High Ratio of Hispanic Residents	High Ratio of Hispanic/Black Residents
Airbnb Reviews per Household	**2.019*****	**0.502**	**0.164**	**0.548**
	(0.521)	(0.514)	(0.676)	(0.427)
Local Rest. Popularity	1.282**	5.907	2.176	3.087
	(0.497)	(3.835)	(1.901)	(2.100)
log(Active Restaurants)	0.014	0.027	0.042	0.025
	(0.021)	(0.042)	(0.031)	(0.023)
log(Hotel Employees)	0.017	-0.031	0.033	0.006
	(0.012)	(0.028)	(0.023)	(0.019)
log(Retail Employees)	0.197**	0.122	0.014	0.067
	(0.092)	(0.098)	(0.170)	(0.123)
Year Fixed Effects	Yes	Yes	Yes	Yes
Constant	4.806***	4.826***	5.678***	5.245***
	(0.648)	(0.646)	(1.184)	(0.830)
Observations	528	275	286	550
R-squared	0.533	0.570	0.502	0.515
Number of zipcodes	48	25	26	50

Note: This table presents the results of Equation 1, which evaluates the impact of Airbnb intensity (Airbnb Reviews per Household) on Restaurant Employment for each subsample of zipcodes with a high concentration of a specific demographic.

Table 19 Heterogeneity of Airbnb Impact (Subsample by Market Structure)

Dep. Variable: log(Restaurant Employment)	(1) High Competition	(2) Medium Competition	(3) Low Competition
Airbnb Reviews per Household	**1.134*****	**0.947****	**0.247**
	(0.320)	(0.406)	(0.449)
Local Rest. Popularity	2.570***	8.410***	3.812
	(0.672)	(1.904)	(3.427)
log(Active Restaurants)	0.060	0.055*	0.079**
	(0.052)	(0.027)	(0.035)
log(Hotel Employees)	-0.000	-0.007	0.063***
	(0.012)	(0.015)	(0.021)
log(Retail Employees)	0.296**	0.243	0.037
	(0.141)	(0.155)	(0.104)
Year Fixed Effects	Yes	Yes	Yes
Constant	4.244***	4.144***	5.159***
	(1.090)	(1.039)	(0.694)
Observations	360	387	378
R-squared	0.690	0.563	0.387
Number of zipcodes	40	43	42

Note: This table presents the results of Equation 1, which evaluates the impact of Airbnb intensity (Airbnb Reviews per Household) on Restaurant Employment for each subsample of zipcodes based on the level of restaurant competition in that zipcode as measured by the HHI for that zipcode's local Yelp restaurant reviews.

Table 20 Airbnb Impact on Restaurant Employment for Cities Beyond NYC

	(1) *All Cities*	(2) *Austin, TX*	(3) *Chicago, IL*	(4) *Los Angeles, CA*	(5) *Portland, OR*	(6) *San Francisco, CA*
Dep. Variable:	log(Restaurant Employment	log(Restaurant Employment	log(Restaurant Employment	log(Restaurant Employment	log(Restaurant Employment	log(Restaurant Employment
Airbnb Reviews per Household	**0.623***** (0.096)	**0.539***** (0.127)	**0.654** (0.465)	**0.780**** (0.305)	**0.641***** (0.168)	**0.462** (0.369)
Local Rest. Popularity	0.231** (0.091)	0.431* (0.210)	0.672*** (0.117)	0.821*** (0.192)	0.108 (0.077)	0.023 (0.068)
log(Active Restaurants)	-0.019 (0.013)	-0.049 (0.043)	-0.013 (0.016)	0.004 (0.024)	-0.003 (0.019)	-0.104** (0.045)
log(Hotel Employees)	-0.020** (0.009)	-0.032** (0.014)	0.021 (0.014)	-0.018 (0.020)	-0.026 (0.020)	-0.001 (0.038)
log(Retail Employees)	0.263*** (0.043)	0.512*** (0.097)	0.189*** (0.067)	0.078 (0.074)	0.218** (0.092)	0.107 (0.071)
City-Year Fixed Effects	Yes					
Year Fixed Effects		Yes	Yes	Yes	Yes	Yes
Constant	5.021*** (0.296)	3.154*** (0.726)	5.403*** (0.473)	6.109*** (0.519)	5.382*** (0.652)	6.791*** (0.583)
Observations	1,926	261	506	468	318	253
R-squared	0.457	0.508	0.300	0.470	0.458	0.590
Number of zipcodes	176	24	46	43	29	23

Note: This table presents the results of Equation 1 applied to Austin, TX; Chicago, IL; Los Angeles, CA; Portland, OR; and San Francisco, CA. It also reports the results of specification which combines all the cities and includes a City Year Fixed Effect.

Table 21 Heterogeneity of Airbnb Impact (Subsample by Demographics) for Additional Cities Beyond NYC

Dep. Variable: log(Restaurant Employment)	(1) Full Sample	(2) High Ratio of White Residents	(3) High Ratio of Black Residents	(4) High Ratio of Hispanic Residents
Airbnb Reviews per Household	**0.594*** **	**0.513*** **	**0.571**	**0.570*** **
	(0.089)	(0.104)	(1.555)	(0.139)
Local Rest. Popularity	0.226**	0.136*	0.015	0.665***
	(0.092)	(0.071)	(1.496)	(0.182)
log(Active Restaurants)	-0.023**	-0.026*	-0.009	-0.015
	(0.012)	(0.013)	(0.022)	(0.024)
log(Hotel Employees)	-0.013	-0.019*	-0.017	0.012
	(0.009)	(0.010)	(0.042)	(0.013)
log(Retail Employees)	0.283***	0.330***	0.313***	0.092
	(0.058)	(0.065)	(0.086)	(0.082)
Year Fixed Effects	Yes	Yes	Yes	Yes
Constant	4.839***	4.608***	4.208***	5.970***
	(0.406)	(0.466)	(0.592)	(0.571)
Observations	1,815	1,254	187	407
R-squared	0.369	0.416	0.146	0.491
Number of zipcodes	165	114	17	37

Note: This table presents the results of Equation 1, which evaluates the impact of Airbnb intensity (Airbnb Reviews per Household) on Restaurant Employment for each subsample of zipcodes with a high concentration of a specific demographic for the additional cities presented in section 7. Column one presentes the full sample of zipcodes in these cities with year fixed effects so that it is comparable (Table 20 uses city-year fixed effects for the full sample.)

Table 22 Heterogeneity of Airbnb Impact (Subsample by Demographics) for Los Angeles

Dep. Variable: log(Restaurant Employment)	(1) High Ratio of White Residents	(2) High Ratio of Hispanic Residents
Airbnb Reviews per Household	**0.410**	**1.136****
	(0.341)	(0.530)
Local Rest. Popularity	0.379	0.665**
	(0.244)	(0.296)
log(Active Restaurants)	0.004	-0.021
	(0.034)	(0.029)
log(Hotel Employees)	-0.051	0.019
	(0.033)	(0.016)
log(Retail Employees)	0.242**	0.010
	(0.093)	(0.094)
Year Fixed Effects	Yes	Yes
Constant	5.182***	6.376***
	(0.703)	(0.641)
Observations	242	275
R-squared	0.453	0.445
Number of zipcodes	22	25

Note: This table presents the results of Equation 1, which evaluates the impact of Airbnb intensity (Airbnb Reviews per Household) on Restaurant Employment for 2 subsamples in Los Angeles based on demographics. Column one presentes the subsample of zipcodes with more than 50% declared as White and Column two presents the subsample with more than 50% declared as Hispanic.