Shared Prosperity (or Lack Thereof) in the Sharing Economy

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This paper examines the potential 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 visitors of a city to vicinities that are not traditional tourist destinations. The novel nature of the home-sharing offering means that visitors are lodging in areas that are not accustomed to tourists and, as such, may not have the underlying infrastructure to fully benefit from their visits. Although visitors generally bring significant spending power, it is ambiguous whether or not the visitors use Airbnb primarily for lodging, thus, not contributing to the adjacent vicinity economy. To evaluate this, we focus on the impact of Airbnb on the restaurant employment growth across vicinities in New York City (NYC). Specifically, we focus on areas in NYC that did not attract a significant tourist volume prior to the home-sharing service. Our results indicate a salient and economically significant positive spillover effect on restaurant job growth in an average NYC locality. A 1% increase in the intensity of Airbnb activity (Airbnb reviews per household) leads to approximately 1.7% restaurant employment growth. We also investigate the role of demographics and market concentration in driving the variation. Notably, restaurants in areas with a relatively high number of White residents disproportionately benefit from the economic spillover of Airbnb activity whereas the impact in their black counterparts is not statistically significant. We validate the underlying mechanism behind the main result by evaluating the impact of Airbnb on Yelp visitor reviews – areas with increasing Airbnb activity 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 exogenous policy recently implemented in New Orleans.

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

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] While much of this attention has focused on the sharing economy's

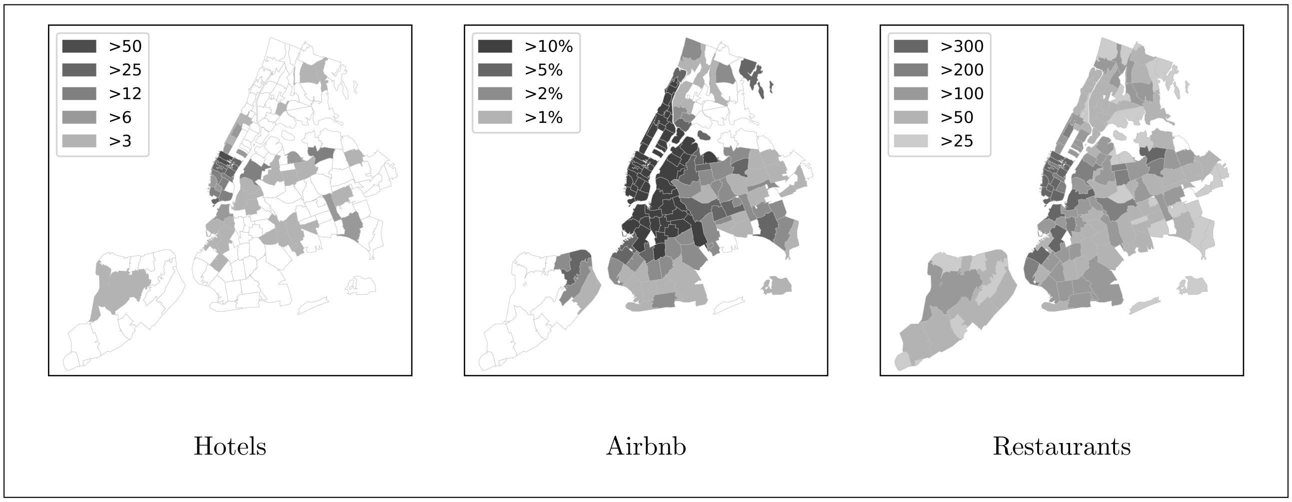
[1] http://time.com/4169532/sharing-economy-poll/

impact on traditional economic activity that directly competes with a platform—e.g., Uber on the taxi industry (Cramer and Krueger 2016, Wallsten 2015), Airbnb on the hotel industry (Zervas et al. 2017), and Airbnb on housing markets in large cities (Barron et al. 2018, Sheppard and Udell 2016), absent concrete empirical evidence, there are equivocal arguments regarding its impact on complimentary economic activities in adjacent vicinities. Related work has documented the effect on entrepreneurial activity (Burtch et al. 2018), purchases in durable goods market (Gong et al. 2018), and interactions between different sharing economy products (Zhang et al. 2018). To fill the void, 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, provide a mechanism to connect residents of a city with potential visitors/tourists by allowing hosts to list their personal homes on the platform. If a visitor chooses to utilize a host's listing, the visitor is given access to the host's home (for the predetermined period) and the hosts receives compensation. By providing access to underutilized inventory (Einav et al. 2016), home sharing platforms have the potential to attract the visitors of a city to vicinities that are not traditional tourist destinations. These locations often don't have a significant hotel presence. Unlike hotels, 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 2016. 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 and not benefit adjacent

Figure 1 Distribution of Hotels, Airbnb Reviews, and Restaurants in NYC in 2016



Note: The figure on the left shows the distribution of hotels across zipcodes in NYC in 2016. The middle figure shows the distribution of Airbnb activity in 2016. The right figure shows the distribution of restaurants in 2016.

vicinities. On the other hand, they may go beyond utilizing the area simply for lodging and spend their tourism dollars at establishments near their Airbnb listings. These establishments would not have access to significant amounts of tourism expenditure without the presence of the home-sharing platform.

While home sharing platforms have an impact on certain types of hotels (Zervas et al. 2017), there are clear distinctions between hotels and home-sharing offerings. The most significant difference is that each individual host, enabled by the broad reach of the internet and the platform, is able to act as an independent entrepreneur. As an individual managing a single room or apartment, the constraints, concerns, and offerings of the home-sharing hosts are significantly different than those of hotels. These distinctions imply that the spillover benefits generally derived by local economies from hotel staying tourists are not as clearly evident for home-sharing visitors.

The first distinction is that home-sharing hosts, not constrained by large fixed costs and land-use regulation, are located in areas where hotels do not traditionally operate. In this study, we focus on whether home-sharing enabled visitors to these type of areas have a meaningful economic impact on local complimentary establishments. Unlike areas that are commonly visited by tourists, these locations do not necessarily have the infrastructure to reap the benefits of tourists lodging in their vicinity. For example, local market structures, cuisine offerings, and crime rates may not be consistent with those generally observed in locations more accustomed to the presence of tourists. The implication is that, while tourists may be willing to lodge in these locations, they are less inclined to make use of the local establishments, especially to an extent where a meaningful economic benefit would be derived.

Since these locations generally do not attract tourists, it is unlikely that they offer a significant presence of tourist attractions. This suggests that the visitors that choose to lodge in these locations will likely spend a significant portion of their time in other areas closer to the popular tourist attractions. Once again, the distinct nature of the home-sharing product means that local complimentary establishments may not obtain significant spillover benefits from these visitors.

The second distinction between home-sharing hosts and hotels is that hosts provide access to residential properties, which predominately have kitchens. This distinction provides the opportunity for home-sharing visitors to forego the local restaurants and cafes, potentially limiting a significant portion of tourist expenditure. This is exacerbated by the fact that Airbnb visitors, specifically ones that choose to share the premises with the host, are price conscious and more likely to utilize such cost saving measures. Moreover, in cases where hosts vacate the premises during the visitors stay, the visitors economic gain in a locality would have to compensate for lost benefits that would have been accrued had the host not left.

On the other hand, there are a multitude of factors which suggest that home-sharing visitors may have a meaningful economic impact, even in areas that are not traditionally visited by tourists. Home-sharing visitors that share the premises with their hosts may be more open to different experiences. This, in conjunction with home-sharing platform motivating their hosts to provide visitors with information on local offerings[2], may persuade visitors to frequent local establishments. Moreover, the continuing growth of the platform suggests that, if home-sharing visitors are more open to different experiences and inclined to follow the host recommendations, there is enough activity to observe a measurable economic spillover benefit. Furthermore, even in the case where

[2] Airbnb hosts can provide their visitors with guestbooks where they outline popular local establishments.

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. As a result, whether home-sharing visitors have a meaningful economic impact in non traditional tourist destinations is an empirical question.

To evaluate the economic spillover effect of home-sharing visitors, 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.[3] Only accommodation ($10 billion) and shopping ($8 billion) expenditures accounted for a higher proportion of tourist spending.[4] As shown in Figure 1, the geographic distribution of restaurants is dispersed across the whole city. This implies that while some areas may 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 a significant number of home-sharing visitors in these areas do dispense the aforementioned tourism expenditure at restaurants near their home sharing accommodations, then these restaurants will have to increase employment to meet the increased demand. This improvement would be reflected in the aggregate area level restaurant employment for a specific area. 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: *Does home-sharing activity have an impact on local restaurant employment growth? If yes, do local factors drive the impact of home sharing on restaurant employment growth?*

To empirically identify the impact of home-sharing visitors on restaurant employment we employ a difference-in-differences (DID) specification which utilizes spatial and temporal variation of Airbnb entry and intensity across zipcodes in NYC.[5] We conduct this analysis on a sample of

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

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

[5] Restaurant employment data is available for the years prior to Airbnb entry into NYC.

NYC zipcodes that were not significant tourist destinations prior to Airbnb entry into NYC and that did not have significant changes in the educational and income profiles of their residents post Airbnb entry. This is discussed in detail in section 3.1. The DID approach extracts the difference in area level restaurant employment before and after Airbnb entry for the first difference. The second difference in the DID framework compares this difference in high intensity Airbnb areas with the analogous difference in low intensity Airbnb areas.

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 a measure of how popular restaurants in an area are among NYC residents. 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. We conduct both static and dynamic matching and find consistent results.

Our results indicate that Airbnb activity has a positive and salient impact on restaurant employment. In terms of magnitude, for an average zipcode, if the intensity of Airbnb activity increases by 1%, then the restaurant employment in that zipcode grows by approximately 1.7%.[6] This result is validated across multiple specifications matching, dynamic matching, and various examinations of the parallel trends assumption necessary for the DID specification (section 3.4). We also conduct various robustness checks to assess the definitions of Airbnb intensity, restaurant employment, aggregation level (NYC neighborhoods instead of zipcodes), and matching metrics. To examine the generalizability of the results to other cities, we expand our analysis to an additional 5 major U.S. cities and find similar results.

We provide support for the mechanism behind these findings by examining the impact of Airbnb activity on Yelp visitor reviews. If Airbnb visitors are frequenting local restaurants in the areas

[6] We use reviews per household as a measure of Airbnb intensity. We discuss this measure in more detail in section 2.1 and assess its robustness in Section C.1.

that do not traditionally attract visitors, then the volume of Yelp restaurant reviews written by visitors to NYC for restaurants in these locations should increase. We find that, on average, if the intensity of Airbnb activity (Airbnb reviews per household) increases by 1%, then the proportion of NYC Yelp visitor reviews that occur in that zipcode increases by approximately 3.4%.[7] The mechanism is corroborated by an examination of a neighborhood level exogenous policy shift that occurred in New Orleans in 2017. New Orleans implemented a policy whereby Airbnb was deemed illegal in one neighborhood while it was officially legalized in adjacent neighborhoods. The policy shift caused the proportion of Yelp visitor reviews in the newly legalized neighborhood to increase and simultaneously decrease in the illegal neighborhood. In summary, our results indicate a three stage process: 1) Airbnb brings visitors to areas that would not otherwise have had access to visitor spending 2) The Airbnb visitors frequent local restaurants in an average neighborhood and 3) The Airbnb visitors that frequent local restaurants in such neighborhoods have a tangible economic impact, measured by employment.

While the average effect across areas is encouraging, it likely masks local area-specific nuances. Since home-sharing brings visitors to a wide range of diverse areas that may substantially differ from traditional tourist locations, all areas may not benefit homogeneously from the spillover effect. In particular, the local restaurant market structure, economic conditions, race and ethnicity of residents vary significantly in non-tourist areas of NYC. Therefore, we examine the role of restaurant market concentration, area income level, and the race/ethnicity of local residents on the spillover effect of home-sharing. We find that the complimentary spillover effect of home-sharing activity on restaurant employment is more pronounced in areas with higher levels of restaurant competition. Notably, we also find that restaurants in areas with a relatively high number of White residents obtain disproportionately higher benefits from the complimentary spillover of home-sharing visitors, while such spillover benefit is weaker, and in fact, statistically not different than zero in majority Black/Hispanic areas. We do not find a large difference in the spillover benefit accrued by poverty-prone and middle-income areas.

[7] This interpretation is obtained by evaluating the impact of a 1% increase in Airbnb intensity for a zipcode with the median proportion of NYC Yelp visitor reviews in 2014.

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 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 the purely 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. Primary Empirical Context

Our empirical context is NYC Airbnb activity and restaurant employment in NYC from the year 2007 to 2016. We aggregate the data at the zipcode level[8] and obtain restaurant employment data from the Bureau of Labor Statistics (BLS) Business Pattern Data.[9] This data provides the number of employees in the restaurant industry by zipcode for a specific year.[10] Our data ends in 2016 as this is the last year of publicly 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.[11] We also obtain zipcode level tax data from the Internat Revenue Services' Statistics of Income (SOI) data set.

2.1. Home Sharing Platform Data from Airbnb

We obtain consumer facing data from Airbnb, the most prominent home sharing platform in the world.[12] Specifically, we gather Airbnb listings and review data for NYC. We periodically gather

[8] We replicate our analysis at the NYC neighborhood level and find consistent results.

[9] The most granular level of data provided by the BLS is the zipcode level. 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

[10] 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. We provide robustness checks to this measure in section C.2 in the Appendix.

[11] We includes all NYC zipcodes with more than 20 restaurants and more than 1,000 households in our analysis.

[12] www.airbnb.com

this data and combine it with data from insideairbnb.com, which is a website providing access to periodic snapshots of Airbnb listings and reviews.[13] 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.[14]

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. Since reviewers are limited to 14 days after their stay to write their reviews and our temporal measure is annual, the timing of a review reflects the timing of the visitors stay. Moreover, the platform makes a concerted effort to motivate reviews as they are necessary for the reputation based matching that occurs on the platform. These incentives result in a significant number of visitors writing reviews. Specifically, using propriety Airbnb data, Fradkin et al. (2019) find that atleast 67% of visitors write reviews. Moreover, using demand data obtained from AirDNA, a company that tracks and sells Airbnb demand data, for 2016 we regress AirDNA actual demand on Airbnb reviews. The R-squared value of this univariate OLS regression is 0.978.

Listings have been used in prior research as well (Barron et al. 2018, Horn and Merante 2017, Zervas et al. 2017) and we examine the robustness of our findings to different measures of Airbnb intensity in Section C.1 in the Appendix. An issue with using listings in our context is that there may be areas with a large number of listings that do not actually attract a significant number of visitors. It is reasonable to suggest that the number of listings might have an impact on the housing prices and/or rental markets given that these listings may have replaced previous tenants. However, if these listings do not attract visitors then there is not a possibility for a spillover for local restaurants. Moreover, it is not unlikely that these sort of biases (that is, areas with plenty

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

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

of listings but little demand) are systematic and correlated to specific area level factors. For this reason, we prefer to use reviews.[15]

2.2. Restaurant Review Data from Yelp

We also obtain consumer facing data from restaurant reviews on Yelp. We collect all public facing Yelp reviews for restaurants in NYC. Yelp reviews have been shown to be indicative of local economic changes (Glaeser et al. 2017), including gentrification (Glaeser et al. 2018). We first utilize the Yelp data as a control for changes in the local economic conditions in a specific zipcode. This follows Glaeser et al. (2017) who find that Yelp data, when used in a model to predict future changes in census data, can explain approximately 29% of the residual variance. Note that this is after controlling for lagged census data. We utilize this documented evidence supporting Yelp as a measure of real-time economic activity and extend it by focusing on Yelp activity related to residents of NYC. This allows us to identify economic developments associated with local residents' behavior changes.

Our Yelp review collection process includes obtaining every review written by each reviewer in our NYC 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.[16] Second, we can separate the reviewers into two categories: 1) reviews written by visitors of 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 erroneous, 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

[15] We recognize that reviews may also be biased. Specifically, listings with more reviews may generate new reviews at a slower pace. However, our results are robust to alternative measures, including listings. Moreover, by aggregating at the zipcode level, we alleviate some of these listing specific review accumulation biases.

[16] 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.

NYC. To resolve this issue, we use the review history of all the reviewers in our sample to identify their locations. To err on the side of caution, we consider a reviewer a "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. We obtain more than 3.5 million Yelp reviews corresponding to 34,331 restaurants in NYC (these include both open and closed restaurants).

In Section 4, we utilize the visitor reviews to examine the underlying mechanism relating airbnb visitors to restaurants. Specifically, if Airbnb users have introduced a significant amount of new restaurant demand to an area, then that demand would be reflected in Yelp visitor activity. 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. Moreover, given the value of Yelp reviews in documenting current economic behavior, we utilize the local reviews to measure restaurant activity by NYC locals. We use this as a control variable in our specifications.

To measure the NYC residents' restaurant activity, we conduct the following procedure. First, for each zipcode (i) and month (t) combination, we calculate the proportion of reviews written by residents of NYC that occurred in restaurants in zipcode i. Specifically, this is calculated as follows: $\frac{\text{\# Yelp Local Reviews in zipcode i during month t}}{\text{\# of Yelp Local Reviews in NYC during month t}}$. Second, for each zipcode, we average all the calculated proportions in a year. We average monthly observations to mitigate the impact of short-term shocks in local preferences that may be due to singular events. For example, restaurants in a zipcode with increases in activity related to a one-time event would potentially benefit, but we would not expect to see significant yearly employment resulting from this short term event. By averaging the monthly data, we are able to focus on the zipcodes with consistent year round changes, implying that these zipcodes may have gone through structural economic improvements. We refer to this variable as *Yelp Local Rest. Activity*.

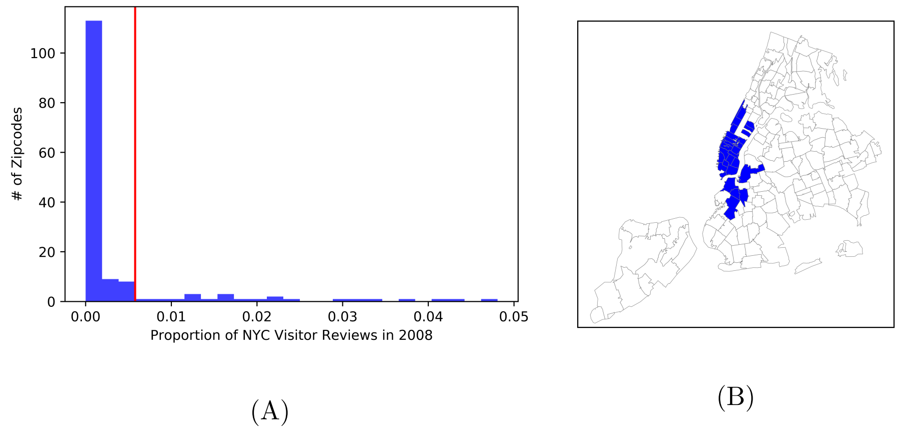
The calculated variable, *Yelp Local Rest. Activity*, captures the time variant area level characteristics that are associated with the popularity of restaurants in an area. For example, if a very popular restaurant was to open in an zipcode in time period $t+1$, then that zipcode would likely see an increase in its share of the overall NYC Yelp reviews written by NYC residents. 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 *Yelp Local Rest. Activity*, we control for the economic variation that causes this new popular restaurant to open in zipcode 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. Sample Construction

NYC is the largest tourist destination in the United States, and, as a result, contains areas that were and continue to be established tourist destinations. 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 with and without 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. Figure 2, panel A, shows the distribution of the proportion of the Yelp visitor reviews for zipcodes in NYC in 2008. We exclude the zipcodes where the proportion of Yelp visitor reviews captured in 2008 is greater than 0.5% (all the zipcodes to the right of the vertical line) and refer to the remaining areas as *NYC Sample 1*. We henceforth refer to areas excluded from *NYC Sample 1* as *traditionally tourist areas*. Thus, areas included in *NYC Sample 1* are considered *traditionally residential areas*. Figure 2, panel B, displays a map outlining the zipcodes that comprise the *traditionally tourist areas*. As expected, these zipcodes are centrally located in southern Manhattan and northwest Brooklyn.

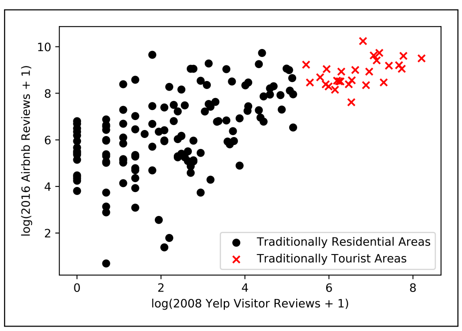
Figure 2 Sample Construction: Traditionally Tourist Areas



Note: Panel A displays the cutoff point based upon the 2008 Proportion of Yelp Visitor reviews for a zipcode to be identified as a traditionally tourist area and therefore be excluded from the main analysis. The main cutoff point is 0.5% (represented by the solid vertical line). Panel B displays a map of NYC with the shaded areas representing the traditionally tourist area.

Figure 3 plots the 2008 Yelp Visitor reviews and 2016 Airbnb reviews in NYC. The plots show that there is very little variation in Airbnb activity among the *traditionally tourist areas*. This indicates that the pre-Airbnb factors that attracted tourists to these areas have a significant role in attracting Airbnb visitors and justifies pruning these areas in our analysis.

Figure 3 2008 Yelp Visitor Reviews / 2016 Airbnb Reviews



Note: Plots the number of 2008 Yelp Visitor reviews in an area by the number of Airbnb reviews in 2016.

By design, the areas in *NYC Sample 1* did not attract a significant amount of visitors in the periods preceding Airbnb's launch. Therefore, for zipcodes in *NYC Sample 1*, the post-2008 visitor activity cannot be related to time invariant area level factors that attract tourists. To account for local changes in the economic environment of an area that may impact restaurant employment, we also identify and exclude areas in *NYC Sample 1* with significant increases in housing construction, income (based on IRS filings), or educational attainment post-2008. We utilize these factors as they have been used previously in research studying gentrification and its impacts (Freeman 2005). We refer to the remaining areas as *NYC Sample 2*, which is the main sample used in our analysis.

3.2. Identification Strategy

Airbnb intensity is defined as the Airbnb reviews per housing unit in a specific year. This measure defines Airbnb intensity throughout this paper. We normalize Airbnb reviews by households to gauge the intensity of Airbnb in a zipcode relative to the population of the zipcode.[17] We utilize the spatial and temporal variation in Airbnb intensity levels across NYC zipcodes[18] to construct the following difference-in-differences (DID) specification which examines the role of Airbnb on NYC restaurant employment:

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

where i represents the zipcode and t represents the year. Our variable of interest is $\frac{Airbnb\ Reviews_{i,t}}{Households_i}$, which is the ratio of the number of Airbnb reviews written for Airbnb listings to the number of households in zipcode i during year t.[19] α_i is a fixed effect for zipcode i which captures time invariant unobserved local characteristics for each zipcode. These include demographic and economic variables without significant year to year changes. For example, if two zipcodes have large differences in the number of households, then this will impact the number of restaurants in the zipcode and, as a result, the restaurant employment. As such, the zipcode fixed effects capture the average level of employment in an area. 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 an event which increases the number of tourists that come to NYC which will positively impact all NYC zipcodes in a year.

[17] We prefer this normalization measure as it captures the relative intensity well. For example, given two zipcodes with 1000 reviews, the impact of the visitors is likely more pronounced in the zipcode with smaller population. Moreover, we prefer this to a normalization of listings per household because, in our context, it doesn't matter whether the visitors are distributed over many listings or clustered among a few listings. In section C.1 in the Appendix we examine the robustness of our results to different measures of Airbnb intensity and find consistent results.

[18] Refer to Figure A.1 in the Appendix for a visual representation of the Airbnb variation across NYC zipcodes.

[19] The denominator in $\frac{Airbnb\ Reviews_{i,t}}{Households_i}$ is time invariant. It is simply to cross-sectionally normalize the size of each area i.

$X_{i,t}$ is a vector of local time varying controls. This includes the *Yelp Local Rest. Activity*, calculated from the Yelp reviews for restaurants in zipcode i. As previously detailed, this variable helps control for variation in restaurant employment that maybe time invariant and independent of Airbnb. We also include local market structure variables from the BLS Business Pattern Data. Specifically, we include the natural log of the number of employees in the hotel industry and the natural log of 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.[20] The number of retail employees controls for the number, size, and performance of retail stores in a local area. This is correlated with improving retail establishment conditions and relates to overall improving economic conditions in an area. Table 1 shows the summary statistics for the variables used in Equation 1.

To further control for time varying local economic and social factors that may impact restaurant employment, it would be useful to include the number of restaurant establishments in area i at time t in $X_{i,t}$. However, since we are examining the potential for Airbnb intensity to impact restaurant employment, Airbnb intensity may also have an impact on the number of restaurants. This will bias our estimates. To alleviate this concern we include the residuals of the following specification in $X_{i,t}$:

$$log(Restaurant\ Establishments)_{i,t} \ = \ \alpha_i \ + \ \delta_t \ + \ \beta_1 \ \cdot \ \frac{Airbnb\ Reviews_{i,t}}{Households_i} \ + \ X^*_{i,t} \ + \ \epsilon^*_{i,t} \quad (2)$$

$X^*_{i,t}$ contains *Yelp Local Rest. Activity*, the natural log of the number of employees in the hotel industry, and the natural log of the number of employees in the retail industry. As a result, the residuals, $\epsilon^*_{i,t}$, captures the unobserved variation in restaurant establishments, after the impact of

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

Table 1 Summary Statistics

		2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Restaurant Employment	Total	61,186	67,086	66,651	68,168	72,317	75,230	80,764	86,204	90,830	96,143
	Median	394	438	437	432	452	508	494	550	600	620
	Mean	506	554	551	563	598	622	667	712	751	795
	St. Dev	372	405	377	380	420	430	486	521	539	571
Airbnb Intensity											
	Median	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.5%	1.1%	2.3%
	Mean	0.0%	0.0%	0.0%	0.0%	0.1%	0.3%	0.8%	2.0%	4.2%	6.4%
	St. Dev	0.0%	0.0%	0.0%	0.1%	0.3%	0.6%	1.4%	3.6%	7.0%	9.7%
Airbnb Reviews	Total	0	1	99	919	3,333	8,291	20,599	54,028	113,728	176,893
	Median	0	0	0	0	0	7	23	82	214	417
	Mean	0	0	1	8	28	69	170	447	940	1,462
	St. Dev	0	0	3	23	64	137	327	892	1,857	2,709
Yelp Local Rest. Activity											
	Median	0.001	0.002	0.002	0.003	0.004	0.006	0.009	0.015	0.021	0.023
	Mean	0.002	0.003	0.005	0.008	0.013	0.016	0.020	0.029	0.039	0.043
	St. Dev	0.002	0.003	0.007	0.013	0.021	0.024	0.028	0.038	0.049	0.054
Hotel Employment	Total	3,207	3,260	3,154	2,994	3,206	3,466	3,558	3,340	3,462	3,542
	Median	2	0	2	2	2	2	2	2	2	2
	Mean	27	27	26	25	26	29	29	28	29	29
	St. Dev	94	93	91	77	83	81	83	74	78	76
Retail Employment	Total	157,146	155,634	154,649	160,895	167,670	171,805	174,062	180,249	187,324	187,831
	Median	1,020	1,064	998	982	1,086	1,100	1,085	1,158	1,146	1,203
	Mean	1,299	1,286	1,278	1,330	1,386	1,420	1,439	1,490	1,548	1,552
	St. Dev	1,131	1,110	1,081	1,108	1,164	1,198	1,197	1,213	1,236	1,215

Note: Summary statistics for the variables included in specification 1 for the zipcodes in *NYC Sample 2*.

Airbnb intensity, local popularity, retail, and hotel employment have been controlled for.[21] We refer to $\epsilon^*_{i,t}$ as *Adjusted Restaurants Count* and include it in $X_{i,t}$ in Equation 1. Finally, the error term, $\epsilon_{i,t}$, in Equation 1 is the unobserved random shock associated with a area (i) during a specific time (t). We calculate robust standard errors that allow $\epsilon_{i,t}$ to be correlated for a specific zipcode i across time t (Moulton 1990).

3.3. Main Results

Table 2 displays the results for the specification in Equation 1 at the zipcode level of analysis. Column 1 shows the results for the analysis which includes all 157 zipcodes in NYC. Column 2 of the table reports the results of the specification in Equation 1 using only the zipcodes identified in *NYC Sample 2* with only Airbnb intensity $\left(\frac{Airbnb\ Reviews_{i,t}}{Households_{i,t}}\right)$, year effects (δ_t), and zipcode

[21] Note that the coefficient in specification 2 for Airbnb intensity is 0.625 and has a p-value of less than 0.001, justifying our concerns. Moreover, we examined the robustness of our results to including log(Restaurant Establishments) directly, and our results remain consistent.

fixed effects (α_t) estimated. Columns 3 adds controls for the local restaurant popularity index and *Adjusted Restaurants Count*. 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 zipcode. The coefficient for the specification estimated with *NYC Sample 2* with all the covariates (column 4) is 1.010. This result indicates that, ceteris paribus, if Airbnb intensity in a zipcode increases by 1%, then restaurant employment will increase by approximately 1.7%.[22]

In Section C.4 of the Appendix, we examine the robustness of our findings to changes in Airbnb intensity measure, restaurant employment measure and also conduct a placebo experiment to examine the potential for spurious correlation. Our results are consistent across all robustness checks. We also estimate all our main results by including a neighborhood-specific quadratic time trend instead of *Yelp Local Rest. Activity* to account for area-specific unobserved trends and find very similar estimates. These results are not reported for brevity but are available on request.

3.3.1. Matching Our results have thus far shown that Airbnb has a positive impact on restaurant employment in NYC. 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 observables. We now incorporate matching to further evaluate the robustness of these finding with regard to any lingering endogeneity concerns associated with 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).

Using the zipcodes in *NYC Sample 2* (121 zipcodes), we use matching to define a subset of the data where zipcodes with significant Airbnb activity are matched with zipcodes without significant

[22] The average number of households in this sample is 19,808 and the associated median is 18,286. Considering the median Airbnb intensity in Table 1, the average year over year increase starting from 2012 is 0.58%.

Table 2 Airbnb Zipcode Level Impact on Restaurant Employment

	(1)	(2)	(3)	(4)
Dep. Variable:	log(Restaurant Employment)	log(Restaurant Employment)	log(Restaurant Employment)	log(Restaurant Employment)
Airbnb Reviews per Household	**0.706*****	**1.206*****	**1.051*****	**1.010*****
	(0.108)	(0.271)	(0.184)	(0.187)
Yelp Local Rest. Activity	-0.106		1.038***	1.107***
	(0.134)		(0.277)	(0.279)
Adjusted Restaurants Count	0.799***		0.737***	0.737***
	(0.063)		(0.072)	(0.074)
log(Hotel Employees)	0.027***			0.020*
	(0.010)			(0.012)
log(Retail Employees)	0.165**			0.034
	(0.066)			(0.068)
Zipcode Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Constant	5.144***	5.993***	5.991***	5.730***
	(0.474)	(0.016)	(0.014)	(0.470)
Observations	1,570	1,210	1,210	1,210
R-squared	0.648	0.488	0.587	0.590
Number of zipcodes	157	121	121	121

*Notes: * $p < .10$, ** $p < .05$, *** $p < .01$. 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 all zipcodes in NYC. Columns 2-4 show the results using NYC Sample 2. Errors are clustered by zipcode.*

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 2016 Airbnb activity to determine whether a zipcode is treated. Based on the distribution of 2016 Airbnb reviews per household (Airbnb intensity), we establish upper and lower treatment criteria. If a zipcode has more Airbnb intensity in 2016 than the upper treatment criterion, then that zipcode is considered treated. If a zipcode has less Airbnb intensity in 2016 than the lower treatment criterion, then that zipcode is considered a control. Zipcodes where the number of 2016 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 zipcode. Zipcodes 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 2016 of each zipcode. We then calculate the 70^{th} percentile of the distribution of 2016 Airbnb intensity levels (5.03%). 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 2016 Airbnb intensity (1.35%). A zipcode with 2016 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 52 zipcodes.

Column 1 of Table 3 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 1%, then restaurant employment would increase by approximately 1.54%.

Table 3 Airbnb Zipcode Level Impact on Restaurant Employment with Matching

	(1)	(2)	(3)
Dep. Variable:	log(Restaurant Employment)	log(Restaurant Employment)	log(Restaurant Employment)
Airbnb Reviews per Household	**0.933*** **	**0.707*** **	**1.043*** **
	(0.220)	(0.265)	(0.262)
Yelp Local Rest. Activity	1.422*	190.569***	188.512***
	(0.726)	(58.367)	(61.520)
Adjusted Restaurants Count	0.747***	0.632***	0.650***
	(0.103)	(0.079)	(0.082)
log(Hotel Employees)	-0.012	0.015	-0.007
	(0.011)	(0.013)	(0.012)
log(Retail Employees)	0.082	0.078	0.066
	(0.117)	(0.086)	(0.092)
Zipcode Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Constant	5.404***	5.448***	5.551***
	(0.805)	(0.591)	(0.627)
Observations	520	592	528
R-squared	0.656	0.606	0.625
Number of zipcodes	52	97	89

*Notes: * p < .10, ** p < .05, *** p < .01. This table presents the results of Equation 1, which evaluates the impact of Airbnb intensity (Airbnb Reviews per Household) on Restaurant Employment with the sample selected using matching. Column 1 shows the results using propensity score matching. Column 2 shows the results with dynamic matching based on a starting set which includes zipcodes in NYC Sample 1 and column 3 shows the same for a starting set which includes zipcodes in NYC Sample 2.*

3.3.2. Matching: Sensitivity Analysis Since the selection of treatment in our design is subjective, we conduct a sensitivity analysis on the upper and lower treatment criteria. Table B.1 in the Appendix 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 2016. 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 2016. For example, the coefficient in the first row and first column represents a minimum treatment threshold corresponding to the 70$^{\text{th}}$ percentile and a maximum untreated threshold corresponding to the 35$^{\text{th}}$ percentile. This entails that only the upper 30$^{\text{th}}$ percentile and lower 35$^{\text{th}}$ percentile of observations (according to 2016 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 1% increase in Airbnb intensity results in an increase in restaurant employment between 1.42% and 1.96% at the zipcode level.

3.3.3. Dynamic Matching The matching approach utilized thus far is dependent upon the following assumption: conditional on the time varying controls incorporated in the model and year fixed effects, an area's attractiveness to Airbnb activity does not change. This implies that two matched areas retain the same level of attractiveness (conditional on controls). To remove the dependency of this assumption and examine the robustness of our results, we also perform dynamic matching to examine the role of time varying economic changes in driving our results. Specifically, we conduct the following procedure:

1. Identify each zipcode/year combination with an Airbnb intensity greater than 2%.[23] We consider these zipcode/year combinations as treated.

2. For each identified zipcode/year combination, using all other zipcodes in the same year as potential controls, conduct nearest neighbor matching (based on propensity score) to match the treated zipcode/year combination with the most similar control zipcode based on the following criteria: (i) Restaurant employment in the previous year. (ii) The number of Starbucks locations in the current year. (iii) The *Yelp Local Rest. Activity* in the current year. (iv) The number of hotels in the current year.

We match on the restaurant employment to find an area with comparable employment in the previous year. We include the number of Starbucks locations as it is often seen as an indicator

[23] The median in 2016 was 2.3%. We conduct various robustness measures around this criteria and find consistent results.

of gentrification and improving economic conditions (Glaeser et al. 2018). We include the local popularity index and the number of hotels to give a measure of the relative attractiveness of an area's restaurants to locals and visitors. Therefore, the comparison is between areas where the restaurant employment in the previous year is similar and the current year variables are also comparable. We estimate specification 1 and include all the dynamically matched zipcode/year combinations. We additionally include all observations for any zipcode that was matched for the period between 2007-2010.[24] The results are presented in columns 2 (dynamic matching on zipcodes in *NYC Sample 1*) and 3 (dynamic matching on zipcodes in *NYC Sample 2* of Table 3 and both indicate a positive and salient impact of Airbnb on restaurant employment.

3.4. Examining the Parallel Trends Assumption

A key assumption of DID specification 1 is that the restaurant employment trends in the periods preceding significant Airbnb activity in an area must be parallel, conditional on controls. To examine the validity of this assumption, we employ two strategies. First, we examine the impact of Airbnb intensity on alternative industries that should not be impacted by visitor activity but should increase with improving economic conditions in an area. Second, we directly test this assumption using the leads and lags model (Autor 2003).

3.4.1. Falsification Industries We identify four industries that should not be impacted by increases in Airbnb intensity: banking services, fitness centers, and hair/beauty salons. All these industries would be expected to experience growth during periods of improving economic conditions that result from changes such as gentrification. However, Airbnb visitors' expenditures should not have an impact on these industries. Columns 1-3 of Table 4 present the results where the dependent variable is the log of employment in these sectors respectively. Reassuringly, the results indicate that Airbnb intensity does not have an impact on any of these industries.

[24] By including the observations for the periods preceding Airbnb entry into NYC, we are able to replicate the DID structure from Specification 1.

Table 4 Falsification Tests

Dep. Variable:	(1) Comm. Banking Employment	(2) Fitness Employment	(3) Beauty Salon Employment
Airbnb Reviews per Household	**0.136** (0.206)	**-0.360** (1.092)	**0.076** (0.172)
Local Rest. Popularity	-0.218 (0.532)	-0.415 (1.944)	-0.138 (0.289)
log(Falsification Industry Establishments)	1.092*** (0.088)	2.124*** (0.123)	1.102*** (0.063)
log(Hotel Employees)	0.004 (0.021)	0.034 (0.043)	0.005 (0.010)
log(Retail Employees)	0.209** (0.095)	-0.103 (0.223)	-0.032 (0.053)
Zipcode Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Constant	0.647 (0.647)	0.991 (1.486)	1.048*** (0.355)
Observations	1,210	1,210	1,210
R-squared	0.475	0.533	0.652
Number of Zipcodes	121	121	121

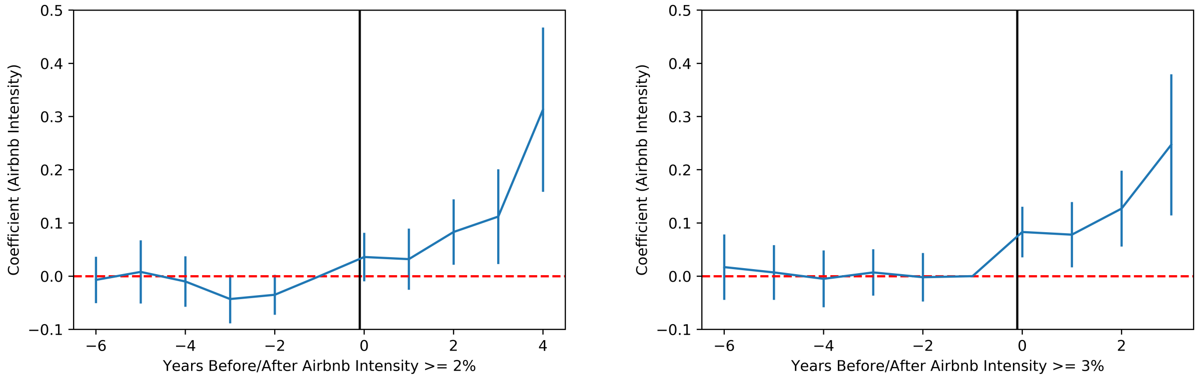
*Notes: * p < .10, ** p < .05, *** p < .01. This table presents the results of the various falsification tests.*

3.4.2. Leads and Lags Model The falsification tests in section 3.4.1 provide support that the parallel trends assumption is not violated. However, we directly test this assumption using the relative time model (leads and lags model). Specifically, we incorporate leads and lags dummies that indicate the temporal difference (in years) between an observation and the time of treatment. Since this test requires a binary treatment variable, we estimate two versions of this model, one with the treatment criterion set at 2% intensity of Airbnb and another set at 3% Airbnb intensity. The model is specified as follows:

$$\begin{aligned} log(Restaurant\ Employment)_{i,t} &= \alpha_i + \delta_t + \sum_j \tau_j \cdot PreAirbnb(j) \\ &\quad + \cdot \delta AirbnbBinary_{i,t} + \sum_k \omega_k \cdot PostAirbnb(k) + X_{i,t} + \epsilon_{i,t} \qquad (3) \end{aligned}$$

Figure 4 provides a graphical representation of the leads and lags coefficients and their estimated confidence intervals. In both versions (2% and 3%) the results indicate that, in the periods proceeding Airbnb activity, there is not a statistically significant difference in the restaurant employment between the Airbnb and non-Airbnb intense areas. However, in the periods after Airbnb intensity reaches 2% or 3%, the impact of Airbnb intensity on restaurant employment is positive, significant, and growing.

Figure 4 Leads and Lags Coefficients



Note: These figures display the coefficients (and confidence intervals) for the leads and lags model presented in section 3.4 for 2% (left) and 3% (right) treatment levels.

4. Evidence Supporting the Validity of the Underlying Mechanism

4.1. The Impact of Airbnb on Yelp Visitor Reviews

Thus far, our results 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:

$$\frac{Yelp\ Visitor\ Reviews_{i,t}}{Yelp\ Visitor\ Reviews_{t}} = \alpha_i + \delta_t + \beta_1 \cdot \frac{Airbnb\ Reviews_{i,t}}{Households_{i,t}} + X_{i,t} + \epsilon_{i,t} \quad (4)$$

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.

In parallel with our restaurant employment analysis, we control for zipcode 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, restaurant local popularity index, and *Adjusted Restaurants Count*. The error term, $\epsilon_{i,t}$, is the unobserved random shock associated with a zipcode (i) during a specific time (t).

Table 5 presents the results of Equation 4. Column 1 of the table reports the results of the specification in Equation 4 for the zipcodes in *NYC Sample 2*. Column 2 reports the results of the matched sample of zipcode. The results indicate that Airbnb has a positive and salient impact on the proportion of NYC Yelp visitor reviews written in a zipcode. To provide economic interpretation for the coefficient (Airbnb Reviews per Household), we evaluate the effect on a hypothetical zipcode where the proportion of NYC visitor reviews is 0.057%—the median value in 2012. If Airbnb intensity, as measured by *Airbnb Reviews per Household*, increased by 1% then the proportion of Yelp visitor restaurant reviews in this zipcode would increase by approximately 0.0023%.[25] Given that the current proportion of NYC visitor reviews is 0.057%, this represents a 4.04% increase in the proportion of Yelp visitor reviews. Furthermore, given that NYC tourist restaurant spending was $7.4 billion in 2012, the extra 0.0023% that would be captured by the median zipcode would translate to approximately $170,000 of extra tourist restaurant expenditure.

We recognize that Yelp restaurant reviews present certain challenges regarding sampling error (individuals that write choose to write reviews are likely very different than those that don't write reviews). Specifically, it can be argued that Airbnb visitors are more likely to write online reviews given their preference of using the online platform to fulfill their accommodation needs. This will cause an upward bias in our estimate. However, if Airbnb users are actually more likely to write reviews, then this fact actually allows us to derive greater faith in the fact that Airbnb visitor will influence Yelp visitor reviews. That is, given this bias, it is important that this result be verified, as it directly links to the underlying mechanism: Airbnb visitors actually visiting restaurants in the vicinity of their Airbnb listing. On the other hand, while less probable, if Airbnb visitors are less likely to write Yelp reviews then this also reinforces this finding as a validation of the underlying mechanism.

[25] This is based on results from matched zipcodes, column 2 of Table 5.

Table 5 Airbnb Impact on Prop. of NYC Visitor Reviews

	(1)	(2)
Dep. Variable:	Prop. NYC Yelp Visitor Reviews	Prop. NYC Yelp Visitor Reviews
Airbnb Reviews per Household	**0.158****	**0.229*****
	(0.064)	(0.060)
Yelp Local Rest. Activity	0.411***	0.696**
	(0.148)	(0.303)
Adjusted Restaurants Count	0.039**	0.055**
	(0.019)	(0.025)
log(Hotel Employees)	-0.000	-0.003
	(0.002)	(0.003)
log(Retail Employees)	0.000	-0.004
	(0.009)	(0.011)
Zipcode Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Constant	0.055	0.082
	(0.061)	(0.078)
Observations	1,210	520
R-squared	0.320	0.491
Number of zipcodes	121	52

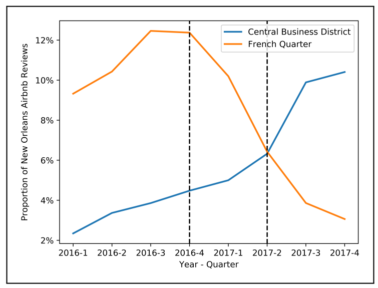
Notes: $* \ p < .10$, $** \ p < .05$, $*** \ p < .01$.

We also estimate equation 2 for the various matching treatment criteria that were explained in section 3.3.1. Table B.2 in the Appendix shows the coefficient for Airbnb Reviews per Household from Equation 4 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. 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.[26] New Orleans officials also claimed that they would fine those hosts that were not in compliance with the new regulation. As a result

Figure 5 New Orleans Airbnb Policy and Airbnb Activity

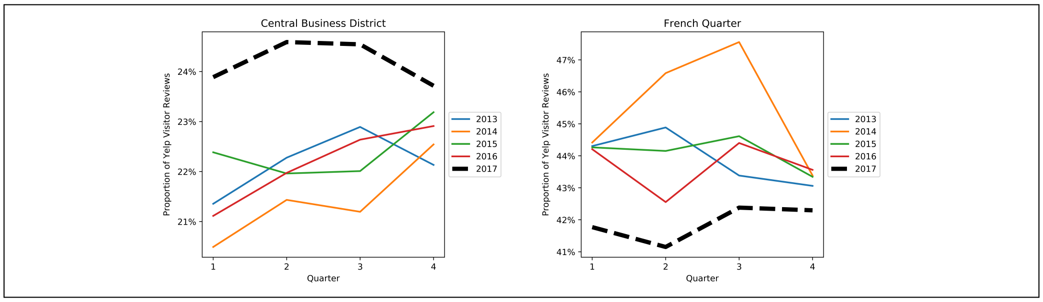


Note: The first dashed line corresponds to the period the New Orleans City Council announced the new Airbnb regulation. The second dashed line is the quarter that the policy was enacted. In the interim, potential hosts were able to register with the city.

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 5 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 indicate 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

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

Figure 6 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.

Airbnb review data for New Orleans. We aggregate this data to the New Orleans neighborhood level based on the neighborhood definitions used by Airbnb. Figure 6 plots the proportion of New Orleans 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 in which 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.

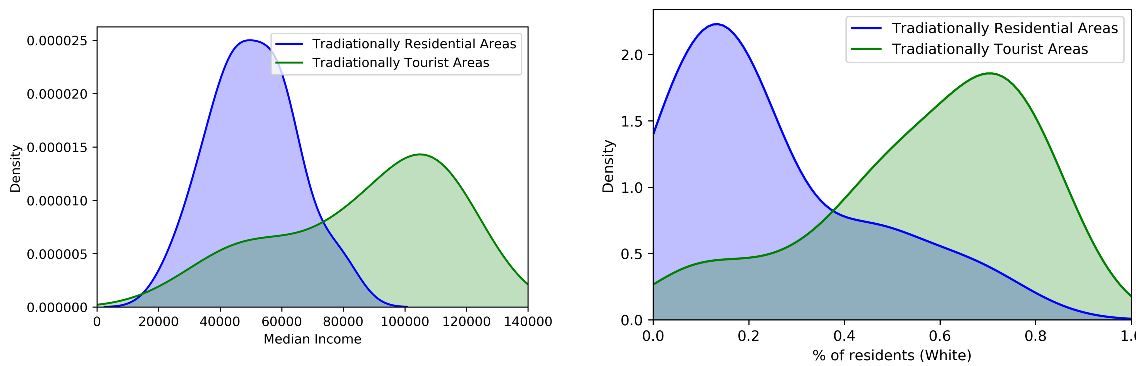
5. Heterogeneity Analysis

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 zipcodes. This evidence suggests that the spillover benefits of Airbnb visitors extend to areas that are not traditionally accustomed to tourists. However, because of the nature of the home-sharing platform, Airbnb availability is distributed across the city. This means that there is significant heterogeneity in the local market structures and demographics of the zipcodes where Airbnb has a footprint. Therefore, while the average impact on NYC zipcodes that are not traditional tourist destinations is evident, it is unclear what role local factors play in determining the existence and magnitude of this spillover. Therefore, we extend our 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 (income and race) and market structure.

5.1. Heterogeneous Impact of Airbnb Due to Local Demographics

We first explore the differences between the *traditionally residential areas* with high levels of Airbnb activity (with greater than 2% –median Airbnb reviews per household– Airbnb intensity in 2016) and the *traditionally tourist areas.* Figure 7 shows the differences in median income and the proportion of White residents. We note significant differences in terms of income and racial distributions between the two areas. One way to examine any impact of the racial and income differences of

Figure 7 Demographic Distribution Differences Between Traditionally Residential and Tourist Areas



Median Income

Prop. of Residents (White)

Note: The left figure shows the distribution of income between the Traditionally Residential and Traditionally Tourist Areas. The right figure show the distribution of the proportion of residents that identified as White based on data from the U.S. Census Bureau.

the non-tourist areas on the Airbnb spillover benefits accrued is to analyze the zipcodes separately based on demographics differences.[27] According to the New York City Government Poverty Measure Report[28], the poverty threshold for household income in 2016 is $32,402. Subsequently, we refer to any zipcode with less than $40,000 median household income as a poverty-prone area. We consider any zipcode with median household income between $40,000 and $60,000 as a middle-income area. The rest are classified as high-income areas.

[27] We use the 2011 American Community Survey from the U.S. Census Bureau to obtain zipcode level data on median household income and race/origin. White refers to White and not Hispanic and Black refers to Black and not Hispanic.

[28] https://www1.nyc.gov/assets/opportunity/pdf/18_poverty_measure_report.pdf

Similarly, for each zipcode, we determine the proportion of residents that identify as White, Black, or Hispanic. Table 6 summarizes the distribution of each demographic for the zipcodes in our sample. We create three subsamples of zipcodes, one for each race/ethnic 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 6 also shows the percentage of zipcodes within each subsample where the Airbnb intensity is high (Airbnb per household is greater than 3% in 2016). The percentages indicate that, while there is variation between the subsamples, they independently have a distribution of Airbnb active and passive zipcodes, which enables us to identify the impact of Airbnb activity in each subsample. For the high-income areas, the Airbnb activity does not have enough variation to identify the impact.

Table 6 Demographic Statistics

Demographic	Zipcode Average	Zipcode Median	Zipcode 75^{th} Percentile	Airbnb Intensity $< 3\%$	Airbnb Intensity $\geq 3\%$ Average
White	31.2%	21.8%	51.8%	75.8%	24.2%
Black	22.9%	11.3%	33.6%	33.3%	66.7%
Hispanic	29.9%	24.0%	43.8%	50.0%	50.0%
Income (<$40K)	$31,259	$32,642	$36,188	48.6%	51.4%
Income (>=$40K ; <$60K)	$50,442	$51,395	$55,120	46.3%	53.7%
Income (>=$60K)	$72,447	$71,811	$77,242	93.3%	06.7%

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 in each demographic subsample.

Table 7 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. The results indicate heterogeneity across subsamples in terms of the benefits derived from the spillover effect of Airbnb. Specifically, the results indicate that, among the selected demographics, areas with a high proportion of White residents benefit disproportionately from the home-sharing platform facilitated visitors. In contrast, the impact is weaker in magnitude and, in fact, statistically insignificant, for predominantly Black or Hispanic areas. Columns 4 and 5 show the results for differences across area level income. The results indicate that the spillover is evident across both economic strata. To better understand the heterogeneity in Airbnb impact we observe based on

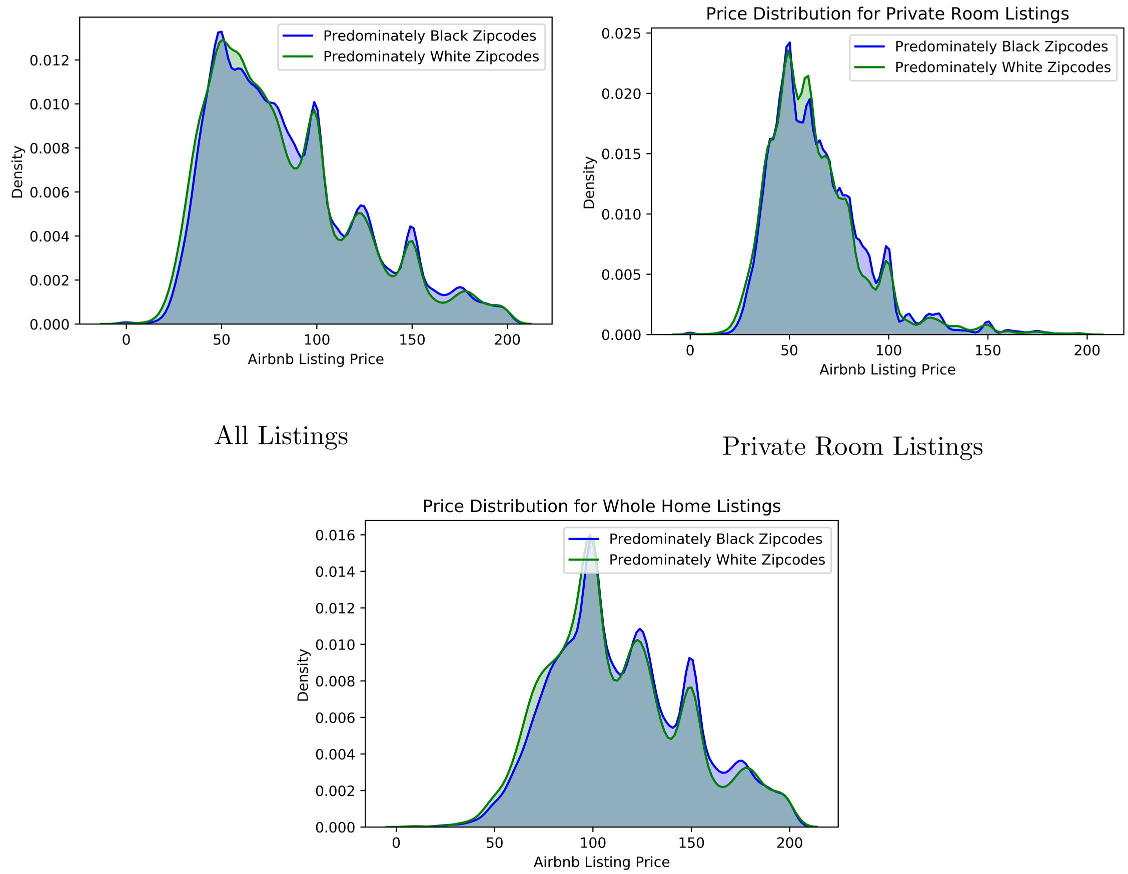
Table 7 Heterogeneity of Airbnb Impact (Subsample by Demographics)

Dep. Variable: log(Restaurant Employment)	(1) High Ratio of White Residents	(2) High Ratio of Black Residents	(3) High Ratio of Hispanic Residents	(4) Income < \$40,000	(5) Income >= \$40,000 < \$60,000
Airbnb Reviews per Household	**2.267****	**0.341**	**0.512**	**0.863*****	**0.908***
	(0.913)	(0.454)	(0.486)	(0.190)	(0.541)
Yelp Local Rest. Activity	0.917**	7.695***	0.270	2.184**	0.981**
	(0.358)	(1.179)	(1.035)	(0.881)	(0.369)
Adjusted Restaurants Count	0.651***	0.500***	0.845***	0.748***	0.757***
	(0.169)	(0.119)	(0.213)	(0.099)	(0.145)
log(Hotel Employees)	0.002	0.026	0.005	-0.007	0.038*
	(0.021)	(0.021)	(0.025)	(0.016)	(0.020)
log(Retail Employees)	0.079	0.009	-0.316**	-0.058	0.031
	(0.133)	(0.092)	(0.130)	(0.109)	(0.083)
Zipcode Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Constant	5.734***	5.566***	8.050***	6.291***	5.816***
	(0.922)	(0.603)	(0.896)	(0.758)	(0.587)
Observations	280	200	220	370	540
R-squared	0.569	0.714	0.486	0.653	0.612
Number of zipcodes	28	20	22	37	54

*Notes: * $p < .10$, ** $p < .05$, *** $p < .01$. This table presents the results of Equation 1 for different subsamples of zipcodes by demographics.*

the racial and ethnic composition of an average area, we next explore potential explanations for the differences. One possibility is that the visitors that frequent predominately Black zipcodes are more price sensitive and have a tighter budget. We look for evidence on budget constraints of the guests by looking at the price distribution of Airbnb listings in both predominantly White and Black areas. Figure 8 shows that there is practically no difference in the price distributions, including when we separate the listings by types (whole homes vs. private rooms). It is important to note that most visitors probably realize the nature of the area they are staying in after going

Figure 8 Price Differences (Predominately White/Black Zipcodes)



All Listings

Private Room Listings

Whole Home Listings

Note: The upper left figure shows the Airbnb listings price distribution differences between listings in areas where residents identify predominately as White and areas where the residents predominately identify as Black. The right and bottom figure display the analogous distributiohns for private room and whole home listings respectively.

there, i.e, ex-post. Consistent with the extensive literature on prejudice, a potential explanation may relate to the perception of crime and lack of safety often associated with areas with a higher proportion of minorities. To examine this potential among Airbnb visitors, we identify Airbnb reviews that contain phrases and words suggesting that the Airbnb visitors felt that the area was unsafe.[29]. We graphically present these results in Figure A.2 in the Appendix. The upper left chart in Figure A.2 shows the distribution of these reviews across the NYC zipcodes whose residents are either majority Black, White, or Hispanic. There is a clear disparity in the proportion of these

[29] Specifically, we identify Airbnb reviews that mention an area as being one of the following: unsafe, dangerous, shady, crime, risky, or seedy

reviews that are associated with Airbnb listings in zipcodes where the majority of residents are Black. We also obtain data from NYC open data initiative on reported crimes and felonies in a zipcode. The upper right chart in Figure A.2 shows the proportion of crimes reported in the zipcodes where the residents are predominately of one demographic and the bottom chart shows the felonies. The distribution of crimes indicates that the Airbnb guests' perceptions are significantly worse than actual reported crime statistics. Moreover, the discrepancy is particularly stark for the predominately Black areas.

The review contents reveal that Airbnb visitors are more likely to discuss negative aspects of a local area that relate to safety if they are staying in a predominately Black zipcode. This may be partly attributed to the ignorance of the Airbnb visitors to the demographic makeup of a specific location while making their reservation.[30] To corroborate this, we examine Airbnb visitors that stayed in NYC more than once. We identify those visitors that stayed in a predominately Black or White zipcode during their first stay. We then calculate the proportion of these visitors that stayed in the same zipcode the second time they visited NYC and used Airbnb. Among these visitors, we find that 13% of visitors that stayed in a predominately Black zipcode stayed in the same zipcode for their second trip. This compares to a 21% retention rate in the majority White zipcodes. This suggests that a larger portion of the visitors that stayed in the predominately Black zipcodes were dissatisfied with their location and chose to change their location for their subsequent visit.

While the findings on racial/ethnic disparity in accruing spillover benefits from Airbnb 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 partially affecting the Airbnb visitor behavior due to less auspicious reasons that relate to food preferences. To ascertain the differences in restaurant offerings, we use the category label for each restaurant from its Yelp.com page. Figure A.3 in the Appendix displays the 8 most common categories in the majority Black, majority White, and *Traditionally Tourist Areas*. A Comparison of the majority White and

[30] Over 60% of Airbnb hosts in the predominately Black areas are not Black.

the *Traditionally Tourist Areas* shows that the categories have significant overlap. The categories are all the same except Mediterranean replaces bars in the majority White areas. However, the *Traditionally Tourist Areas* and the majority Black areas are significantly different in their offerings. Specifically, Carribean, Seafood, and Soulfood make up almost half of the proportions in the majority Black areas, but are not in the top 8 in the *Traditionally Tourist Areas*.

5.2. Heterogeneous Impact of Airbnb due to Restaurant Market Structure

The competitive nature of the restaurants in a locality may also impact 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, areas with a more competitive restaurant dynamic have a multitude of restaurants that are popular. This implies that visitors may distribute to these restaurants and, as a result, all the restaurants obtain small increases in activity. Given that these restaurants were already popular and likely had significant local activity, it is unclear whether areas with more competition and, as a result, greater diversity in visitor restaurant activity, would necessarily increase restaurant employment to appease this new demand.

To determine the competitive dynamics among the restaurants in a specific zipcode, we calculate the Herfindahl-Hirschman Index (HHI).[31] The market share of each restaurant is calculated using the share of the local Yelp reviews written in 2011 (Gutt et al. 2019). 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 standards adopted from Justice Department, we identify high competition (HHI $\leq$ 1,000), medium competition (HHI between 1,000 and 1,800) and low competition (HHI $\geq$ 1,800) zipcodes.

[31] 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.

Table 8 shows the results of Equation 1 on the three subsamples of varying local restaurant competition. The results indicate that the spillover impact of Airbnb is strongest in the areas with high competition (column 1). 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 physical 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 physical capacity.

Table 8 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	**1.262***** (0.234)	**0.114** (0.441)	**0.652** (0.992)
Yelp Local Rest. Activity	1.207*** (0.279)	0.586 (2.689)	-3.218 (4.149)
Adjusted Restaurants Count	0.550*** (0.093)	0.904*** (0.152)	0.892*** (0.158)
log(Hotel Employees)	0.000 (0.013)	0.058** (0.024)	0.034 (0.025)
log(Retail Employees)	0.094 (0.075)	0.217 (0.174)	-0.145 (0.120)
Zipcode Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Constant	5.633*** (0.531)	4.148*** (1.145)	6.311*** (0.776)
Observations	730	230	250
R-squared	0.641	0.621	0.546
Number of zipcodes	73	23	25

*Notes: * p < .10, ** p < .05, *** p < .01.*

6. 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.[32] We aggregate the data at 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. 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. Column 1 of Table B.3 in the Appendix 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 B.3 present the results. They show that the impact of home sharing and restaurant employment is consistent for all cities.

7. Conclusions and Discussion

As home sharing platforms have gained popularity, they have been met with resistance from local regulators and other stakeholders 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-entrepreneurs who are monetizing inventory that would otherwise have remained stagnant (rooms in their homes or whole homes when they are traveling) 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.

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

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 attract 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 zipcode increases by 1%, then restaurant employment would increase by approximately 1.7%.

Our employment growth estimates compare favorably with a back-of-the-envelope calculation. Specifically, there were 113,728 Airbnb reviews in *NYC Sample 2* in 2015. Considering that 67% of visitors wrote reviews (Fradkin et al. 2019), this amounts to approximately 170,000 visits. If we assume that, on average, each visit consists of two individuals and the visitors stay for two weeks (the average stay indicated by Airbnb), then this results in approximately 340,000 Airbnb visitors and 9,500,000 meals per year.[33] A typical restaurant has 100 seats, requires 22 employees, and expects the patrons to spend considerable time in eating their meals (Batt et al. 2014). As such, we assume 5 meals per day per seat for each restaurant which translates to approximately 23 meals serviced per employee. Therefore, the number of additional full-time employees needed to serve the Airbnb visitors in 2015 is approximately 1,130 (9,500,000 meals per year / 365 days / 23 meals per employee). Given that there were 86,204 restaurant employees in 2014, this suggests a 1.3% increase in restaurant employment in 2015. Reassuringly, this is remarkably close to the estimates from our model.

A question that is important in this context is whether this increase in restaurant employment in the *traditionally residential areas* is coming at the cost of employment in the *traditionally tourist areas*. There are two main possibilities: 1) The home-sharing visitors who are frequenting *traditionally residential areas* would have stayed in the *traditionally tourist areas* without the home-sharing platform or 2) The home-sharing visitors would not have come to NYC if not for the

[33] 340,000 visitors x 2 meals per day * 14 days = 9,520,000.

home-sharing platform. The most plausible reality is that home-sharing visitors are a combination of both possibilities. In 2016, *traditionally tourist areas* accounted for approximately 51% of the Airbnb reviews in our data. Figure A.4 in the Appendix displays the restaurant employment growth in these areas during the period of our study and indicates positive restaurant employment growth throughout the years we study. Figure A.4 also displays the growth rates in *traditionally residential areas* with and without high levels of Airbnb intensity (high Airbnb areas correspond to areas with higher than 3% Airbnb intensity in 2016). The *traditionally residential areas* with significant Airbnb presence have the highest growth rate (especially after 2012, which is when Airbnb activity significantly increases). However, the restaurant employment growth rate in the *traditionally tourist areas* remains positive.

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. 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 effect of an Internet-enabled phenomena—sharing platform induced visitor redistribution—on the actualized economic impact of complimentary services—restaurants.

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 might 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.

References

Autor DH (2003) Outsourcing at Will: The Contribution of Unjust Dismissal Doctrine to the Growth of Employment Outsourcing. *Journal of labor economics* 21(1):1–42.

Barron K, Kung E, Proserpio D (2018) The Sharing Economy and Housing Affordability. *Working Paper* .

Batt R, Lee JE, Lakhani T (2014) Of human resource practices, turnover, and customer service in the restaurant industry. Technical report, School of International & Public Affairs, Columbia University New York City, NY.

Brynjolfsson E, Hu YJ, Rahman MS (2009) Battle of the Retail Channels: How Product Selection and Geography Drive Cross-Channel Competition. *Management Science* 55(11):1755–1765, ISSN 0025-1909.

Burtch G, Carnahan S, Greenwood BN (2018) Can You Gig It? An Empirical Examination of the Gig Economy and Entrepreneurial Activity. *Management Science* .

Caliendo M, Kopeinig S (2008) Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys* 22(1):31–72, ISSN 09500804.

Coles PA, Egesdal M, Ellen IG, Li X, Sundararajan A (2018) Airbnb Usage Across New York City Neighborhoods: Geographic Patterns and Regulatory Implications. *Working Paper* .

Cramer J, Krueger AB (2016) Disruptive Change in the Taxi Business: The Case of Uber. *American Economic Review* 106(5).

Dehejia RH, Wahba S (2002) Propensity Score-Matching Methods for Nonexperimental Causal Studies. *Review of Economics and Statistics* 84(1):151–161, ISSN 0034-6535, URL `http://dx.doi.org/10.1162/003465302317331982`.

Edelman B, Luca M, Svirsky D (2017) Racial Discrimination in the Sharing Economy: Evidence from a Field Experiment. *American Economic Journal: Applied Economics* 9(2).

Einav L, Farronato C, Levin J (2016) Peer-to-Peer Markets. *Annual Review of Economics* 8(1):615–635.

Filippas A, Horton J (2017) The Tragedy of your Upstairs Neighbors: When is the Home-Sharing Externality Internalized. *Working Paper* .

Forman C, Ghose A, Goldfarb A (2009) Competition Between Local and Electronic Markets: How the Benefit of Buying Online Depends on Where You Live. *Management Science* 55(1):47–57, ISSN 0025-1909.

Fradkin A, Grewal E, Holtz D (2019) Reciprocity in two-sided reputation systems: Evidence from an experiment on airbnb .

Freeman L (2005) Displacement or Succession? Residential Mobility in Gentrifying Neighborhoods. *Urban Affairs Review* 40(4):463–491.

Glaeser EL, Kim H, Luca M (2017) Nowcasting the Local Economy: Using Yelp Data to Measure Economic Activity. *NBER Working Paper No. 24010* .

Glaeser EL, Kim H, Luca M (2018) Nowcasting Gentrification: Using Yelp Data to Quantify Neighborhood Change. *Working Paper* .

Gong J, Greenwood BN, Song Y (2018) Uber Might Buy Me a Mercedes Benz: An Empirical Investigation of the Sharing Economy and Durable Goods Purchase. *Working Paper* .

Gutt D, Herrmann P, Rahman MS (2019) Crowd-driven competitive intelligence: Understanding the relationship between local market competition and online rating distributions. *Information Systems Research* .

Heckman JJ, Ichimura H, Todd PE (1998) Matching As An Econometric Estimator Evaluation. *Th Review of Economic Studies* 65(2):261–294.

Ho DE, Imai K, King G, Stuart EA (2007) Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference. *Political Analysis* 15.

Horn K, Merante M (2017) Is home sharing driving up rents? Evidence from Airbnb in Boston. *Journal of Housing Economics* 38.

Iacus SM, King G, Porro G (2012) Causal Inference without Balance Checking: Coarsened Exact Matching. *Political Analysis* 20:1–24.

Imai K, King G, Stuart EA (2008) Misunderstandings between experimentalists and observationalists about causal inference. *Journal of the Royal Statistical Society* 171(2):481–502.

Kogan L, Papanikolaou D, Seru A, Stoffman N (2017) Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics* 132(2):665–712.

Moulton BR (1990) An Illustration of a Pitfall in Estimating the Effects of Aggregate Variables on Micro Units. *The Review of Economics and Statistics* 72(2):334, ISSN 00346535.

Quattrone G, Proserpio D, Quercia D, Capra L, Musolesi M (2016) Who Benefits from the "Sharing Economy" of Airbnb? *International World Wide Web Conference. WWW* .

Rosenbaum PR, Rubin DB (1983) The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika* 70(1):41–55.

Seamans R, Zhu F (2013) Responses to Entry in Multi-Sided Markets: The Impact of Craigslist on Local Newspapers. *Management Science* 60(2):476–493.

Sheppard S, Udell A (2016) Do Airbnb properties affect house prices? *Working Paper* .

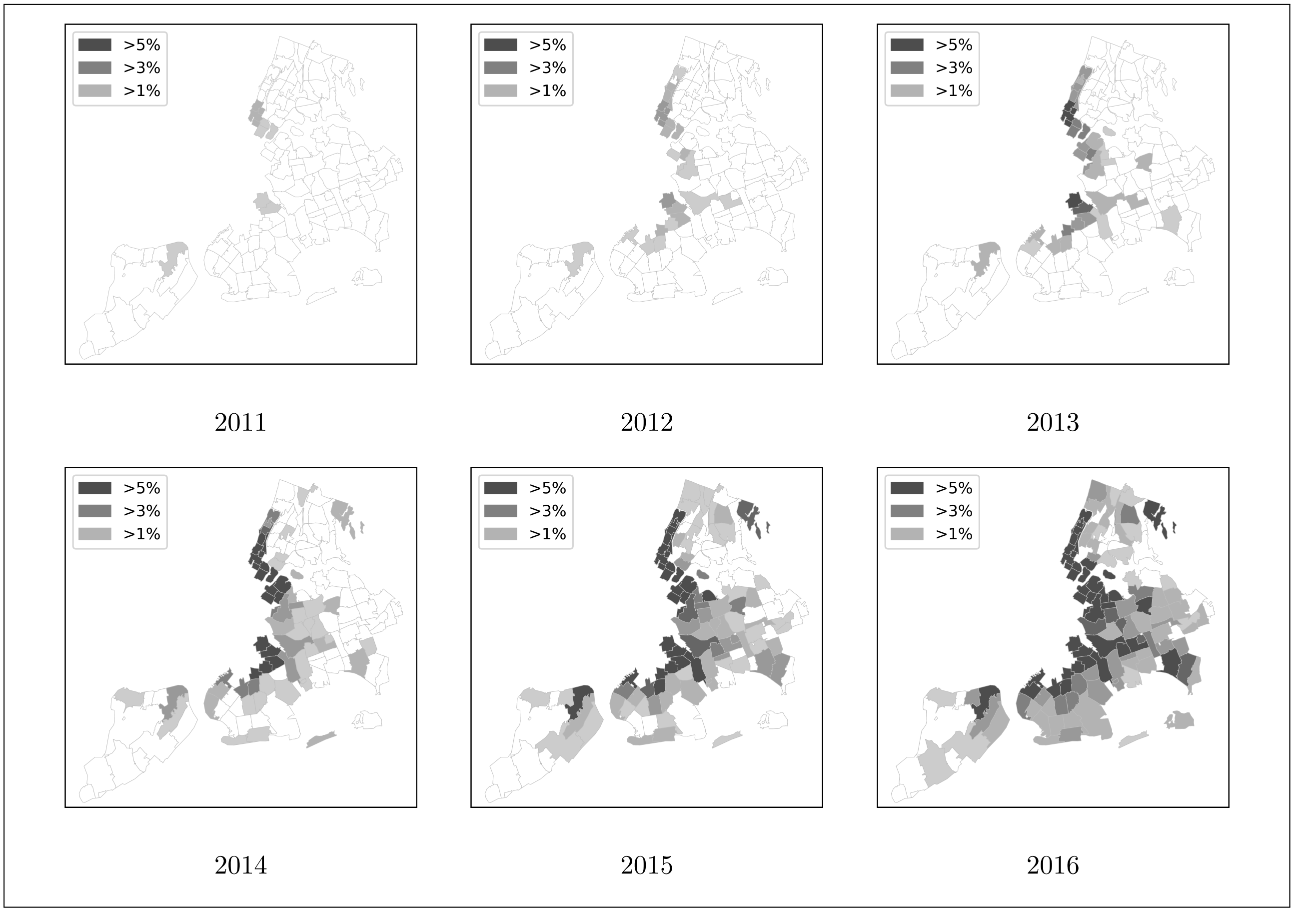
Wallsten S (2015) The Competitive Effects of the Sharing Economy: How is Uber Changing Taxis? *Technology Policy Institute* .

Zervas G, Proserpio D, Byers JW (2017) The Rise of the Sharing Economy: Estimating the Impact of Airbnb on the Hotel Industry. *Journal of Marketing Research* 54(5).

Zhang S, Lee D, Singh PV, Mukhopadhyay T (2018) Demand Interactions in Sharing Economies: Evidence from a Natural Experiment Involving Airbnb and Uber/Lyft. *Working Paper* .

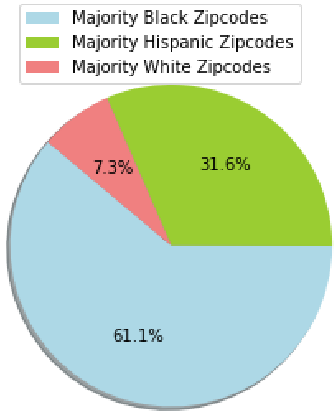
Appendix A: Figures

Figure A.1 NYC Zipcodes and Airbnb Intensity for NYC Sample 2

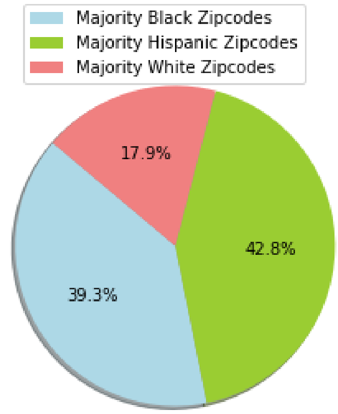


Note: Shows the spatial and temporal variation in Airbnb intensity, measured by Airbnb reviews per household, for NYC zipcodes in *NYC Sample 2*.

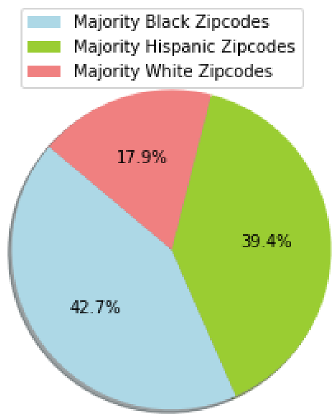
Figure A.2 Airbnb Reviews and Crime Distribution



Airbnb Reviews Mentioning Safety Concerns



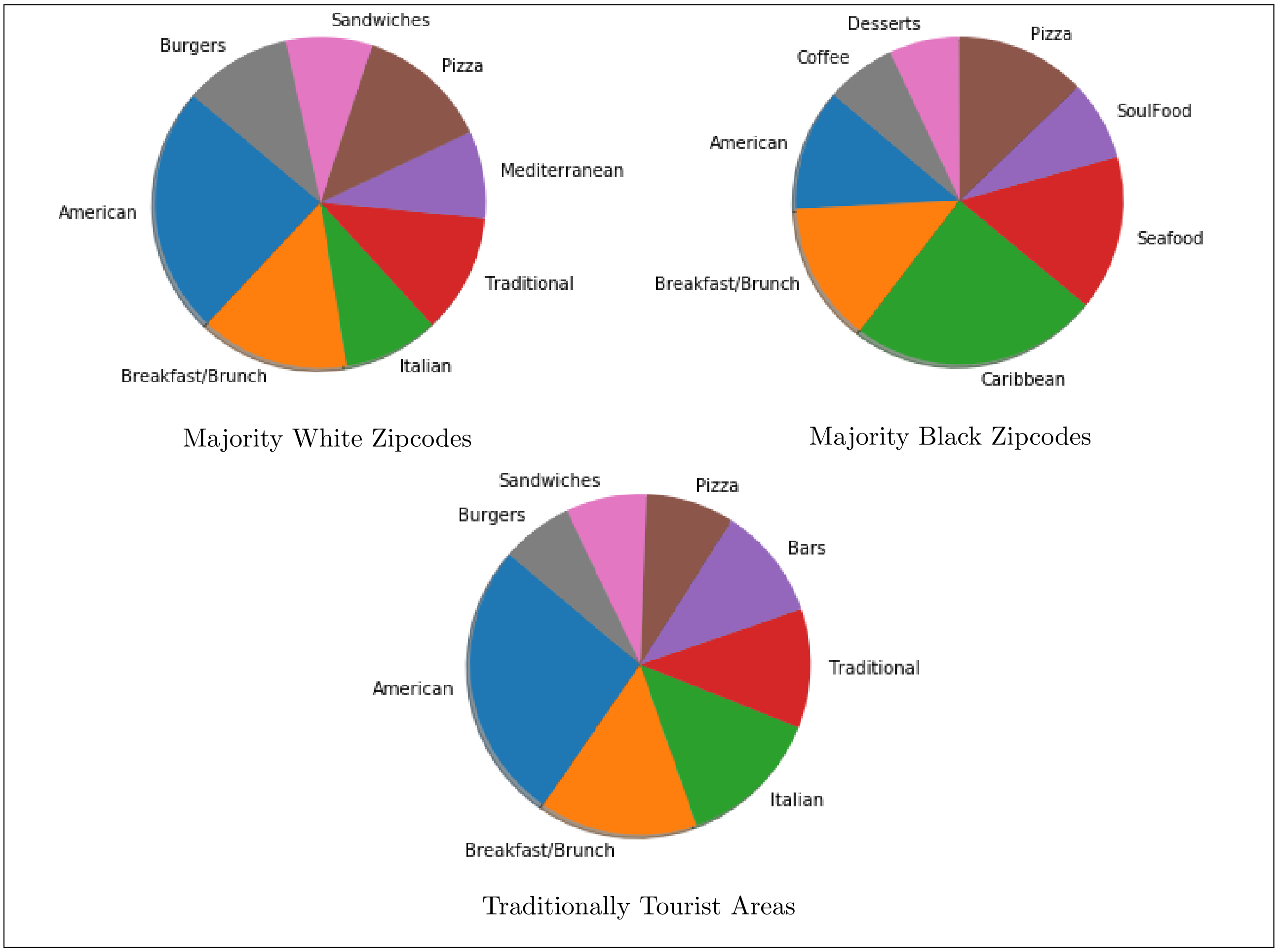
NYC Crimes Reported



NYC Felonies Reported

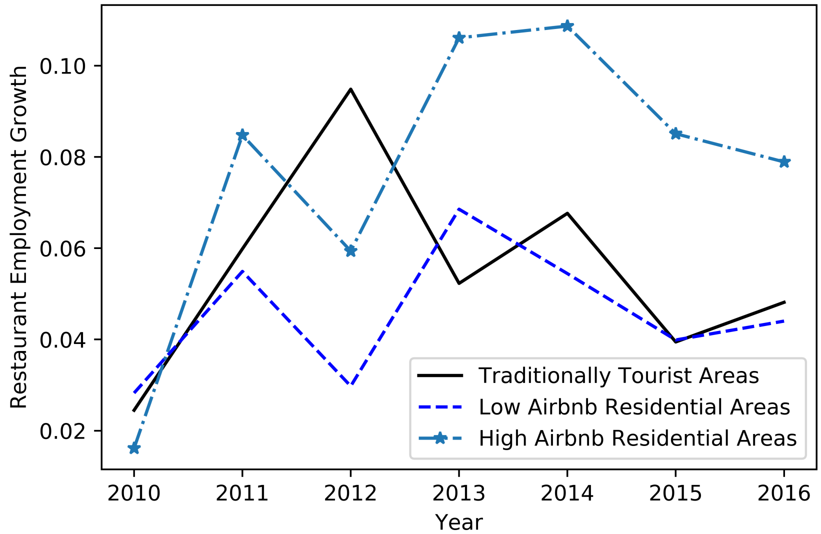
Note: The upper left figure displays the distribution of Airbnb reviews across NYC zipcodes (by demographics) that mention an area as one of the following: unsafe, dangerous, shady, crime, risky, or seedy. The upper right figure displays the proportion of all crimes (either misdemeanor or felony) that were reported across NYC zipcodes by the demographics of the zipcodes.The lower figure displays the proportion of felonies that were reported across NYC zipcodes by demographics of the zipcodes.

Figure A.3 Yelp Restaurant Category Distribution for NYC Zipcodes



Note: The pie charts in this figure show the 8 most referenced restaurant categories for different NYC areas and their proportions. The upper left figure shows the categories for the majority White zipcodes in NYC. The upper right and lower graph show the categories for the majority Black zipcodes and the *Traditionally Tourist Areas.*

Figure A.4 Restaurant Employment Growth



Note: This figure plots the restaurant employment growth in NYC. High Airbnb Residential Areas are traditionally residential areas where the Airbnb intensity measure was greater than 3% in 2016.

Appendix B: Tables

Table B.1 Matching Sensitivity Analysis for Airbnb Treatment (Dep. Var.: Restaurant Employment)

		Lower Treatment Percentile				
		$35^{\text{th}}\%$	$40^{\text{th}}\%$	$45^{\text{th}}\%$	$50^{\text{th}}\%$	$55^{\text{th}}\%$
Upper	$70^{\text{th}}\%$	0.933***	0.994***	0.903***	0.908***	1.046***
Treatment	$65^{\text{th}}\%$	0.938***	0.882***	0.972***	0.993***	0.971***
Percentile	$60^{\text{th}}\%$	1.019***	1.048***	0.973***	1.020***	1.086***

*Notes: * $p < .10$, ** $p < .05$, *** $p < .01$.* 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 2016 is greater than the 70^{th} percentile for all zipcodes and less than the 35^{th} percentile for untreated zipcodes.

Table B.2 Matching Sensitivity Analysis for Airbnb Treatment (Dep. Var.: Proportion Yelp Visitor Reviews)

		Lower Treatment Percentile				
		$35^{\text{th}}\%$	$40^{\text{th}}\%$	$45^{\text{th}}\%$	$50^{\text{th}}\%$	$55^{\text{th}}\%$
Upper	$70^{\text{th}}\%$	0.229***	0.233***	0.212***	0.217***	0.236***
Treatment	$65^{\text{th}}\%$	0.232***	0.234***	0.217***	0.228***	0.243***
Percentile	$60^{\text{th}}\%$	0.233***	0.237***	0.219***	0.219***	0.226***

*Notes: * $p < .10$, ** $p < .05$, *** $p < .01$.* 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 4 is presented for different specification of treatment and control.

Table B.3 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	**0.473*** **	**0.461*** **	**0.282*** **	**0.539*** **	**0.489*** **	**0.299**
	(0.053)	(0.052)	(0.073)	(0.119)	(0.069)	(0.191)
Local Rest. Popularity	0.013	0.005	-0.069	0.628***	0.449**	-0.031
	(0.030)	(0.150)	(0.075)	(0.127)	(0.179)	(0.026)
Adjusted Restaurants Count	0.954***	1.075***	1.012***	0.793***	0.728***	1.236***
	(0.065)	(0.199)	(0.098)	(0.117)	(0.102)	(0.256)
log(Hotel Employees)	-0.013**	-0.000	0.004	-0.034*	-0.023**	-0.003
	(0.007)	(0.014)	(0.011)	(0.018)	(0.010)	(0.025)
log(Retail Employees)	0.156***	0.190***	0.204***	0.154***	0.103*	-0.065
	(0.025)	(0.064)	(0.041)	(0.053)	(0.055)	(0.079)
Zipcode Fixed Effects Yes	Yes	Yes	Yes	Yes	Yes	
City-Year Fixed Effects	Yes					
Year Fixed Effects		Yes	Yes	Yes	Yes	Yes
Constant	6.033***	5.595***	5.417***	5.653***	6.275***	7.868***
	(0.187)	(0.468)	(0.295)	(0.400)	(0.393)	(0.634)
Observations	1,650	240	460	430	290	230
R-squared	0.655	0.719	0.580	0.680	0.710	0.706
Number of zipcodes	165	24	46	43	29	23

*Notes: * p < .10, ** p < .05, *** p < .01.* 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.

Appendix C: Further Robustness Checks

C.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, log transformations are problematic when the number of Airbnb reviews is small (i.e., using a log transformation, an increase in Airbnb reviews from 4 to 8 would be given greater importance than it warrants). This problem is exacerbated in our setting due to annual aggregation leading to 10 observations per zipcode. While the ratio of Airbnb reviews to households does not suffer from this problem, we replace the independent variable in Equation 1 with a variable that takes on the following values: 0 if the ratio of Airbnb to households is less than 2%, otherwise its value is equal to *log(Airbnb Reviews)*. Column 1 of Table C.4 shows the results for this specification and indicates that the results are robust to this alternative definition.

We also examine the robustness of our results to including a binary treatment definition for Airbnb activity instead of the continuous measure used thus far. Specifically, we create a binary variable that has a value if 0 if the Airbnb reviews per household for a specific zipcode/year combination is less than 1%, otherwise the variable has a value of one. We also construct a secondary binary variable that has a cutoff point of 2%. Columns 2 and 3 of Table C.4 show the results for these specifications. Finally, since listings have been used in prior literature as well, in column 4 we use Airbnb listings per household as the measure of Airbnb intensity. The results indicate the our findings are robust to differing Airbnb intensity measures, including strict binary measures of treatment.

C.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,

Table C.4 Robustness Check: Alternative Definitions for Airbnb Intensity

	(1)	(2)	(3)	(4)
Dep. Variable:	Airbnb Measure (1)	Airbnb Measure (2)	Airbnb Measure (3)	Airbnb Measure (4)
Airbnb Intensity Measure	**0.012*** **	**0.059*** **	**0.089*** **	**0.585*** **
	(0.003)	(0.022)	(0.023)	(0.086)
Yelp Local Rest. Activity	1.284***	1.407***	1.284***	0.902***
	(0.317)	(0.330)	(0.314)	(0.262)
Adjusted Restaurants Count	0.766***	0.772***	0.765***	0.716***
	(0.077)	(0.077)	(0.077)	(0.073)
log(Hotel Employees)	0.022*	0.023**	0.023*	0.021*
	(0.012)	(0.012)	(0.012)	(0.012)
log(Retail Employees)	0.056	0.062	0.060	0.020
	(0.069)	(0.069)	(0.069)	(0.068)
Year Fixed Effects	Yes	Yes	Yes	Yes
Constant	5.573***	5.529***	5.547***	5.825***
	(0.475)	(0.475)	(0.471)	(0.470)
Observations	1,210	1,210	1,210	1,210
R-squared	0.586	0.585	0.586	0.592
Number of zipcodes	121	121	121	121

*Notes: * $p < .10$, ** $p < .05$, *** $p < .01$.* This table presents robustness checks for the definition of Airbnb intensity in Equation 1. Column 1 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 2 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 3 is the same as column 2 except the threshold of Airbnb reviews per household is 2%. Column 4 shows the results for a definition of Airbnb that uses active listings per household.

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 C.5 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.

C.3. 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 C.6 and C.7. The results indicate a similarly positive and salient impact of Airbnb on

Table C.5 Robustness Checks: Alternative Definitions for Restaurant Employment

	(1)	(2)
Dep. Variable:	log(Restaurant Employment)	log(Restaurant Employment)
Airbnb Reviews per Household	**0.927*****	**1.053*****
	(0.197)	(0.198)
Yelp Local Rest. Activity	1.181***	1.160***
	(0.334)	(0.316)
Adjusted Restaurants Count	0.729***	0.757***
	(0.081)	(0.081)
log(Hotel Employees)	0.024*	0.023*
	(0.014)	(0.013)
log(Retail Employees)	0.060	0.065
	(0.082)	(0.076)
Year Fixed Effects	Yes	Yes
Constant	5.378***	5.381***
	(0.565)	(0.524)
Observations	1,210	1,210
R-squared	0.518	0.539
Number of Zipcodes	121	121

*Notes: * p < .10, ** p < .05, *** p < .01.* 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.

restaurant employment, alleviating potential concerns regarding the selection of distance metric in our matching analysis.

Table C.6 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	$70^{th}\%$	0.860***	0.839***	0.851***	0.764***	0.882***
Treatment	$65^{th}\%$	0.895***	0.901***	0.842***	0.887***	0.850***
Percentile	$60^{th}\%$	0.886***	0.970***	0.986***	0.934***	0.922***

*Notes: * p < .10, ** p < .05, *** p < .01.* 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 2016 is greater than the 70^{th} percentile for all zipcodes and less than the 35^{th} percentile for untreated zipcodes.

Table C.7 Robustness Check: Matching (using CEM) Sensitivity Analysis for Airbnb Treatment (Dep. Var.: Restaurant Employment)

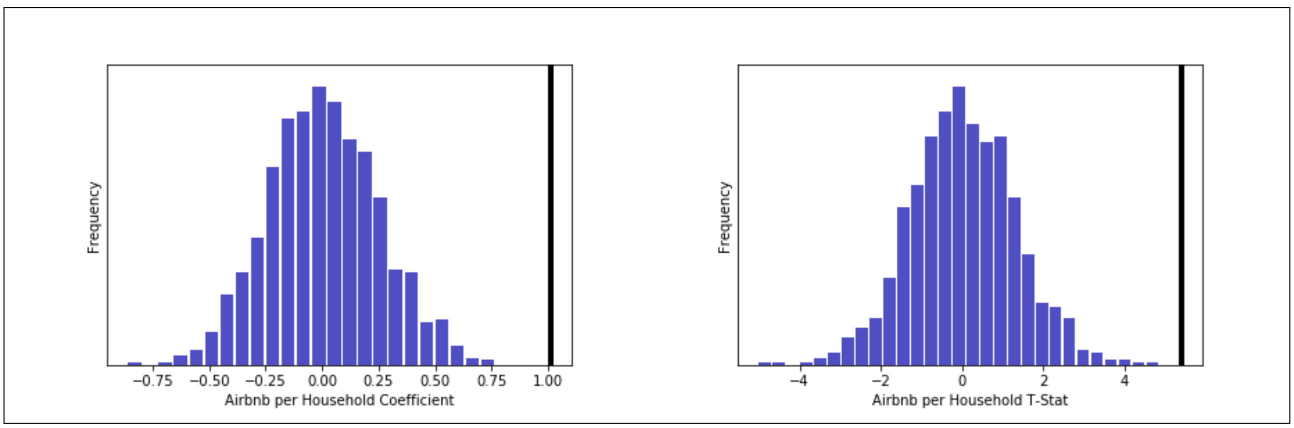
		Lower Treatment Percentile				
		$35^{th}\%$	$40^{th}\%$	$45^{th}\%$	$50^{th}\%$	$55^{th}\%$
Upper	$70^{th}\%$	0.957***	0.996***	0.788***	0.832***	0.870***
Treatment	$65^{th}\%$	0.950***	0.988***	0.780***	0.819***	0.858***
Percentile	$60^{th}\%$	1.086***	1.110***	0.905***	0.914***	0.967***

*Notes: * p < .10, ** p < .05, *** p < .01.* 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 2016 is greater than the 70^{th} percentile for all zipcodes and less than the 35^{th} percentile for untreated zipcodes.

C.4. 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 similar to Kogan et al. (2017). Specifically, for each zipcode, we first extract the yearly Airbnb intensity (Airbnb reviews per household). Since we have 121 zipcodes in our main sample, this means we have 121 Airbnb intensity temporal patterns. Moreover, since we use 10 years of data, we have 10 observations per zipcode. Keeping the within zipcode patterns constant, we randomly shuffle the 121 Airbnb intensity temporal patterns across the zipcodes. We replicate this 1,000 times. Figure C.5 plots the distribution of the resulting coefficient values and t statistics. Both distributions are centered around zero and, relative to the effects we find in Table 2, it is unlikely that our results are spurious.

Figure C.5 Effect of New Orleans Airbnb Policy on the Proportion of Yelp Visitor Reviews



Note: This figure plots the distribution of the coefficients (left panel) and t-statistics (right panel) from estimating equation 1 for 1,000 placebo experiments. The vertical black line corresponds to the coefficient and t-statistic from our main specification.